Computational Intelligence for Dynamic Route Planning in IoT-connected Autonomous Vehicle Networks

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1. Introduction

In this IoT-connected vehicular network, a robotic system is distributed at the global scale and oriented towards establishing Robot-Enabled Networks for personal mobility but also anywhere else alongside the roads; hence, denoted in future versions of the paper as the Internet of Things-connected Autonomous Vehicle Networks, IV-AN or simply Autonomous Vehicle Networks, AN. [1] The Internet of Vehicles (IoV) has attracted considerable attention from the wireless communication and vehicular networking research communities, and its subdomains are multitier networks of entities that represent the composite structure of a cognitive and cooperative Cyber-Physical System, as a Complex IoT—Internet of Things—connected Autonomous Vehicle Networks (IoT-connected Autonomous Vehicle Network—IoT-Connected AN or simply AN), as introduced in this paper after performances using Global System for Mobile Communications (IoV–IV–AN—Internet-Connected AN)3 contributions. Finally, this article has as thesis—definition—formula the top-level objective on what means the next pillar of the "Smart Car" deployed under the umbrella called a lot later Robot-Enabled Networks, where the global robotic clouds are directly perturbing the robotic clouds of the interconnected "IV-AN ND" (Navigation Devices) class of real-car human-oriented systems.

[2] Intelligent Transport Systems (ITS) have created a new domain called the Internet of Things-connected Autonomous Vehicle Networks, where autonomous vehicles communicate with each other in the form of an interconnected network. [3] In this paper, the efficient IEEE Internet of Vehicles (IoV) platform is studied, where a vehicular ad hoc network of vehicles is connected with the Internet in a seamless manner: not only do the vehicles have dedicated and augmenting sensors and devices for their IT (called Internet in the Vehicles-oriented

Internet-connected or Internet of Vehicles—IoV), but also they have Internet sensors and devices that are of interest to them in terms of environmental, calming and entertaining facts according to their actions and positions on the Earth (called the Internet of Things-connected Autonomous Vehicle Networks or addressed just Autonomous Vehicle Networks for short). An evolutionary variant of this IoT-connected vehicular ad hoc network introduces the robotic constellation of the above-considered networks with augmented connectivity towards the Internet and autonomy for taking decisions. The main objective is to model by extending the existing IoT–IV–AN formal framework the hybrid variant that is denoted by IoT–IV–AN–DC and that is presenting a completely new topic for research in the field of systems of this complexity.

1.1. Background and Significance

The aspect and the possibility of the proper operation of Intelligent Transportation Systems (ITS) in a changing environment have been widely discussed. In many studies, the term dynamicity was analyzed from the point of view of advanced driver assistance systems (ADASs) features, like active steering control, autonomous driving, digital twin-based soft computing techniques to minimize the complexity and access spatiotemporal dynamicity, shared mobility transportation services, route-based design approaches for transportation service networks, and transportation safety, security, and privacy concerns in the context of autonomous and intelligent vehicles (AVs/AIVs), especially IoT-connected ones, which benefited from this combination of original potentiality analysis, mainly on the cybersecurity issue [4]. Dynamicity was also analyzed in the coating and enveloping of printed labels on vehicles; material for labelling vehicles is multi-layered, and in the context of the piston movement in vehicles while switching to the second fuel mode in dual fuel engine vehicles.

The concept of intelligent transportation systems (ITS) includes the field of transportation systems, which deals with the use of modern information and communication technologies, computing power, sensors, and devices to improve road transport, road safety, and monitor road traffic in general. Among the most important goals of ITS are the improvement of road safety, the reduction of traffic congestion, and the resulting negative effects (including environmental and economic ones) on urban ecosystems [5]. Automation of transport systems promotes the idea of using autonomous vehicles in the public and private transport of the future without the participation of a driver. In the context of studies on autonomous vehicle networks (connected and automated vehicles, CAVs), real vehicular scenarios experience the dynamism of network topologies, the mobility of neighboring vehicles/roadside units (RSUs), communication quality variations, vehicle heterogeneity, continuous appearances and disappearances of new requests, etc. [6].

1.2. Research Objectives

The main goal of this research is to utilize the available technologies and latest communication paradigms to provide dynamic and safe route guidance services to road users, navigating in IoV environment [7]. The prime focus is on the integration of all latest IoV concepts, such as sensor and communication technologies, seamless integration of V2I communication, and other dynamic route planning algorithms, to provide optimized, fuel-efficient, and safe route-navigation services to vehicles [8]. This navigation service will be used in various ITS services including emergency vehicle navigation, road user categorization, and intelligent routing techniques, in order to provide an efficient navigation service to the user in IoV environment. Now a days, traffic monitoring, energy resource saving, and optimized route planning into a specific traffic environment is very necessary to ensure the safety and user satisfaction. This research project aims to integrate the IoV communication and computational intelligence to predict and optimize the traffic congestion and road blockages, along the most relevant road path to calculate the most efficient road path by incorporating several dynamic road related parameters to compute the most efficient vehicle routing recommendation [9]. This routing service priority will consider the pollution minimization, electric Vehicles (EVs) and HEVs optimized path algorithm to be implemented to prolong the vehicles' travel range in IoV.

1.3. Structure of the Work

The recent investigations in the area have suggested the use of various established and emerging computing paradigms to model transportation networks to capture complex interdependencies and variations inside the network layers. A policy suggestion for dynamic system control, optimization of parameters in transportation networks, and case studies about intelligent transportation systems have been integrated based on the obtained results. Here, we aim to propose a methodological and computational policy, using models constructed via machine learning algorithms by data collected from various sources, to control transportation networks in real-time to obtain sustainable transportation systems. From the vast literature from 1999 to 2017, clustering, optimization, and game theory have been the main strategies for transportation network research, with learning algorithm-based research lagging behind.

For machine learning, support vector machines, neural network models, were also dominant paradigms.

Exploration in IoT-assisted autonomous vehicle landscape has recently gained significant popularity due to availability and reliability of sensory data from traffic infrastructure [10]. The major contributing factors include the prospering telecommunication sector, the newly emerged computing paradigms, e.g. cloud and edge computing, high computational power of multi-core processors and GPUs, and the maturation of machine learning models which are now capable of handling large-scale data. This has made it possible to learn complex relations to create and train models that offer state-of-the-art accuracy in prediction, classification, and optimization tasks. Machine learning models can be trained to provide run-time guidance to vehicles to select a route from the spectrum of dynamically changing roads based on the current traffic situation [5].

2. Fundamentals of Autonomous Vehicles

Accordingly, some research works have been dedicated to understand the implications and optimality of the data-sharing mechanisms percolating through the interior wireless IoT. For instance, the work in demonstrates how data-exchange on IoT can be broken down to a four-tiered dataflow, namely, a low-level dataflow may be complemented with the roadmap for issuing a message from the cabin controller until it is understood by another bodily connected AV, and a high-level dataflow may be anticipated at the system level to yield the optimal message payload and frequency within an IoT-connected platoon of AVs, taking into consideration the optical communications plus differential buffer and energy constraints based on various layers of marshalling between exteroceptive sensors and IoT-based information. Furthermore, not to be overlooked is that the complete mobility environment for IoT can also embody the digital twin (DT-lifefinder) of the originating environment, be it i) a smart destination (smart city or smart highway) that shares internet services with the onboard network of each connected AV this side of the managed destination, or ii) the vehicular exterior environment that communicates via cyber-to-vehicle communication with the connected vehicle's driverless navigation.

Real-time, coordinated, and automated route planning for AVs to adaptively handle unpredictable events (e.g., traffic congestion, roadblocks, parking spots, and refuelling/charging facilities) is of great importance to improve the travel experience of passengers and usability of urban AVs. Leveraging the increasing capabilities offered by sensor and communication technologies [11], how the future AVs will communicate and cooperate autonomously to achieve those goals is the focus of a range of ongoing studies [10]. Connected AVs, as presented in Figure 1, are enabled over the wireless communication infrastructure of the Internet of Things (IoT) [12]. Although the public safety insurance and traffic regulations will require those vehicles to be equipped with a core set of onboard publishing and subscribing functionalities (i.e., V2V), they will also benefit greatly from using IoT-connected devices.

2.1. Definition and Components of Autonomous Vehicles

The IoT technology facilitates augmented mobility assistance; synchronous, dynamic and intelligent vehicle mobility support and required vehicle communication that improvises human, as well as vehicular security. Increasing and dynamic traffic is generating a major concern needed to be addressed that would require sensitive, human-inspired intelligence with extreme fast response in the CAVs variety domain. Thus, for identification, Virtual Market Environment (VME) brings the flexibility and research in terms of trust for assigning resources of the nature of advertising reinforcement-based importance as required [9]. Aiding distributed, dynamic, and odd traffic navigation in Civil AV brings challenges invited by their real-life problems; such as, cooperative nature and different orientation with respect to the supporting infrastructure (road, traffic signal, traffic decoration), latent intention detection, the vehicle-to-everything (V2X) coupling communicated challenges, and their frequent characterization uncertainty. The traffic management productivity requires the end-to-end real-time, human-inspired dynamic route planning and coordination, latency responsive with reasonable computational costs, and the traffic-decreasing ideas.

The term 'IoT sensor networks' in the single vehicle domain are anticipated with sensors inside or attached to the vehicle (e.g. on board diagnostic - OBD, wheel speed sensors, cameras, GPS). The sensors equipped in the autonomous vehicle for localization, mapping, mobility, and security are considered to be part of the IoT-based components of autonomous vehicles. An autonomous vehicle system consists of integrated and coordinated components such as communication systems of user sensors, actuators, driving controllers, and i/o interfaces running on and connected to the internet and mode internet connected vehicles, which established IoT-based systems and provide data management for realtime operational support [13]. In this work, we design dynamic route planning schemes in CAVs networks by exploiting the C-V2X communication feature, allowing the CAVs networks to incorporate perceived traffic information and dynamic network topology control through a communication network to resolve overall network constraint time dependently.

2.2. Challenges and Opportunities in Autonomous Vehicle Technology

Smartcity problems can be real-world optimisation problems. Inspired by this, the work tackles some of classical smartcity problems such as: (1) Traffic congestions; (2) Pollution; and (3) Shortest path optimization for multiple cars in a smart city [14]. The network provides realistic environment and especially the possibility of modeling the traffic. The network also provides state of the art 2D obstacle avoidance characteristics which can be leveraged for 3D simulation of reality, etc. Thus, the network however also enables 3D real models visualisation which for example can be used to provide realistic 3D models of smart city environment such as VR environments, car diagnosis, etc.

Algorithms such as Dijkstra and A* are among the most commonly used for generating paths in traditional autonomous vehicle (AV) technology using static environments [15]. However, these methods fall short in dealing with the complications of dynamic environments. In the AV domain, the work extensively leverages specific heuristics tailored for specific traffic infrastructure while proposing a novel approach to vehicular trajectory estimation obtainable from the network level data [12]. Furthermore, the work proposes a method that conducts optimisation so that vehicles can cooperate in the optimised road networks. Additionally, the work examines parameter selection within a multi-layered representation that uses various types of road network information to provide the shortest possible paths. The authors predict traffic flow and select the most efficient path based on both macroscopic traffic flow prediction and real-time traffic monitoring.

3. Internet of Things (IoT) in Autonomous Vehicles

These varied entities are now realize various desired objectives such as route privacy, trajectory privacy, and journey privacy so as to incentivize vehicles. One of the strong motivations for the current work attracts its significance in how spatially diverse requirements like vehicular networking, mobility and lifecycle support. The existing IoT structure in standard CAV operations as outlined in Ref. [16] utilized usual vehicular networking and vehicle learning fairways of research subjects during peak hours to understand V2V messages with roadside nodes and vehicle driving statuses (e.g., position and velocity information).

V2I communication can be better facilitated through the central cloud as such dynamic route planning effect. V2I communication can be facilitated through Internet-connected edge intelligent transportation systems (ITS) [17]. This network now enables implementational services that range across a spectrum of such enhanced navigation platforms which are extended in achieving intelligent connected vehicles (ICVs). As outlined in Ref., that new integrated entities include vehicle augmented personal mobility systems (vPMS), vehicle cooperative augmented personal mobility systems (CvPMS), and vehicle participative augmented personal mobility systems (PvPMS).

In the advent of the Internet of Things (IoT), dynamic route planning, and the wide-area and local system it is equipped with not only exist as standalone IoT nodes having their own sensory attributes and data processing capability, but can also absorb each other's sensory attributes [18]. Dynamic route planning can absorb locally generated probability models and real-time information sources for traffic pattern maintenance and sensor guidance. By definition, IoT is a concept that refers to connected entities of varied nature undergoing dynamic changes while relying on the edge and core interaction to deliver services in an affordable and efficient manner. IoT can interconnect different kinds of entities—vehicles, infrastructure, drivers and traffic administrators—thus forming a connected society and producing a so-called dumbbell shape (S1) corresponding to vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication loops. Any message exchange between any two nodes constitutes V2X (where X indicates road performance analysis, vehicular networking).

3.1. IoT Architecture and Components

There are two entities in the application layer: the IoV service and the smart city service. The latter one is, in fact, the passive extension of the IoV service, which will be protocol mapped, physically routed, and then managed to deliver services to the Internet. Both entities of these services will harvest the data from vehicles, mesh with vehicle data coming from the Coordinative Computing Layer to support complex decision making, write feedback to vehicles, and cooperate to serve the driver and urban managers at all times. For example, artificial intelligence realizing the operation of autonomous vehicles needs to synthesize enough mental perception to make planning decisions and to implement the motion control process. The action and decision-making process of autonomous vehicles corresponds to the coordinated computing layer, and the successful implementation of this section needs to be supported by the sensing perception and operation control platforms from the other two layers, as well as the coordinated transportation fleet, if we focus on the road surface driving environment. Mutual observations or help can be achieved through the microservice mechanism. For instance, vehicle safety warnings are derived from the feedback of urban road side geographic features and artifacts, the coordinated platform can adaptively obtain a sufficient semantic description.

This paragraph discusses the proposed IoT architecture and components, consisting of a four-layer stratus of sensing, network access, coordinative computing, and application layers. Meanwhile, IoV, as an important part of IoT, reflects the in-depth interaction between people, vehicles, road side units (RSUs), and web services, among others [19]. The IoV applications generally cover the whole process from sensing to perception, planning, scheduling, and control, forming a complete sensing-based control loop. For a driving-centric IoT architecture, the network access layer bundled the in-vehicle network and communication system as one user side, while the other two links among vehicles (V2V), vehicles and RSUs (V2I), and vehicles and web servers (V2X) are considered as the cloud in the IoT architecture. The vehicle perception layer contains various sensors and related fusion algorithms to monitor the traditional driving environment, taking GPS, Inertial Measurement Unit (IMU), camera, LiDAR, and radar sensors as examples [10]. The coordinating computing layer is responsible for fusing data from different vehicles, or from vehicles and infrastructure, to produce the driving environment. Commonly used technologies include DSRC and Cellular V2X (C-V2X). Apart from normal data transmission, C-V2X supports edge computing, which is transforming cloud computing to the edge of the network. An open standard defined LTE-based V2X technologies for different communication modes at the beginning, while its later releases had been gradually evolving to 5G V2X [20]. Meanwhile, cloudlet will be deployed at the intersections to alleviate the backhaul traffic, and multiple micro-clouds will be employed in the urban feeders and collectors to improve the performance of edge computing in this distribution network.

3.2. Applications of IoT in Autonomous Vehicles

Given that the effective management of urban traffic helps in promoting environmental protection, social equity, and a vibrant economy, a wide range of planned, ongoing, and deployed implementations—primarily grounded on Vehicle-to-Everything (V2X) communications and the Internet of Things (IoT) — has been progressively facilitating the incorporation of vehicle-free driving transitions into Intelligent Transport Systems (ITS) that support the operation of CAV [21]. Along similar lines, the existing road network becomes increasingly saturated due to the incessantly increasing number of vehicles, overwhelming demand for parking spaces, heightened negative effects of congestion, and implications associated with accidents and road incidents. Providing Performance Tests of typical use cases, a functional test between IoT-based and cloud architectures is presented, underscoring an open research question on the need for numerous possible theoretical, performance-related, and practical validations. The ecosystem lends context to the cloud platform as the pivot of cooperation among various other sub-systems. As a Post-State-of-the-Art (Post-SOTA) offering, the association between Software-Defined Networking (SDN) and Vehicular Ad-hoc Networking (VANET) is included in this book chapter, as is the state-of-the-art discussion on IoT, 5G, and the future course of IoCV/CAV connected infrastructureonomies.

Autonomous Vehicles (AV) directly depend on Intelligent Transportation Systems (ITS) to reduce multiple factors that impact drives, such as transit time, fuel consumption, and carbon emissions. In this case, ITS is crucial in taking decisions for traffic management in autonomous vehicles, avoiding congestion in the road transport systems. In recent decades, with the growth of the internet, advancements in telecommunication technologies, and recurrent increases in vehicular performance, the trends in traffic management in Intelligent Transportation Systems have shifted towards traffic optimization in the presence of connected autonomous vehicles [18]. In this context, the emergence of Intelligent Transport Systems (ITS) and vehicular communications technologies have underpinned the development of an Internet of Connected Vehicles (IoCV), emerging as an Infrastructure-to-Vehicle and Everything-to-Everything (xE2X) ecosystem. Therefore, this chapter gives an overview on the technologies from which the vision is built, the ITS challenges that are permeating its development and the sensor and computational infrastructures that sustain it. We then, expose the main approaches to dynamic route planning and define a roadmap for future research on the subject, as a guide for the development of successful ITS in the future.

4. Dynamic Route Planning in Autonomous Vehicles

Dynamic route planning in the context of autonomous vehicles entails adjusting routes in real-time to avoid new traffic jams and minimize travel times. The new paradigm introduced in this section via [22] and [23] includes improving the mobility of autonomous vehicles, optimizing driving conditions by adjusting the speed of each vehicle to follow a dynamically-changing itinerary. As communication technologies have been evolving, communication-based issues also have become important to increase driving autonomy. The intelligent edges compute the decision at once without considering those dynamic and the edge-based computing power to be low.

The evolution of artificial intelligence and machine learning has contributed to the development of autonomous vehicles. Autonomous vehicles require accurate and dynamic navigation and reliable communication to automate tasks. Currently, the interest for developing smart cities where mobility can be managed and various services and amenities based on smart city applications can be developed is arising. New solutions are necessary for finding optimal route plans to deliver goods in real-time, thus augmenting the importance of routing algorithms and data-related optimization to provide valuable insights and derive new insights from IoT devices generating large volumes of real-time data [1]. Hence, in the future, autonomous vehicles should consider IoT-generated global variables.

4.1. Traditional vs Dynamic Route Planning

Old traditional route planning methods used static data and only rarely updated maps based on the historical data. However, for the modern scenario, they are severely limited as traffic operates dynamically. Because of this, dynamic route planning (DRP) has gained a great deal of traction, with DRP now commonly used in online route planning systems around the web [24]. In this paper, we propose and evaluate a novel DRP system in the context of the Internet of Things for urban and motorway scenarios. Specifically, we simulate an online route planning system being run on data centers distributed across the city or motorway of interest, where each data center is responsible for collecting and processing local sensor data as well as controlling and managing locally-connected AVs.

Traditional route planning consists of fixed, predefined routes selected based on an existing map – a map created and managed by various government agencies [25]. These routes are influenced by the maximum peak hour or daily traffic loads, as well as projected routes based on historical traffic data. In contrast, dynamic route planning (DRP) suggests routes based on the real-time data measured by several data centers connected by IoT devices. A drawback of conventional route planning is the limited scope, drawn from historical and other static data.

Taking the existing traffic condition into account when planning a route can make a significant difference in the traffic flow.

4.2. Challenges and Requirements

Dynamic and time-dependent challenges of implementing route optimisation for dynamic IoT or autonomous vehicle networks include the need for an up-to-date view of the road network (traffic conditions, hazards, and sensor perception) for real-time operation [26]. This imposes strict computational constraints on the route planning algorithm in terms of computation time overhead because the sensor-perceived road view can change at any time or update cycles can be long. The decomposed architecture of pipeline or agent-based algorithms with modular navigation is desirable with sensor data being converted to final infrastructure-based command signals using real-time deep learning along the automated vehicle network route [27]. Given the dynamic nature of virtual traffic lights and message TTL values in IoT networks, concerns about data grinding and latency for queueing packets, energy/communication budgeting, and data throughput are the primary challenges for planning and navigation strategies to consider while operating in stable or extreme network dynamics with connected tethered vehicles 'popped into' or communicated with via edge IoT gateways [2]. Another challenge is to find real-time edge algorithmic solutions for the IoT feedback loop to optimise driving input, such as minimising fuel consumption or minimising CO2 production for battery and internal combustion propulsion system choices. These algorithms can work in concert with companion mobile, PC, or edge-side apps presenting HMI data for global determinism in passengerconnected autonomy with full access to increasingly customisable take-me-anywhere drive-space.

5. Computational Intelligence in Autonomous Vehicles

Collaborations among HMI (human–machine–interaction) and social routes that manage and predict traffic scenarios can design engagement policies, validate policies, and measure user validation [5]. When C2X technologies are used, IoT plays a key role in solving the complications of transportation in smart cities, particularly traffic congestion. Furthermore, Intelligent Mobility (IM) services, which have come into play, need to interact with CPS and IoT. In CPS, real-world devices and physical objects are integrated with the ICT systems, which can perceive events and support the development of interactive services for the users that are connected by social networks. In summary, motivation is developed to collect suitable travel options for transit routing and so improve trip attributes such as travel time, distance, etc. To attain Intelligent Mobility (IM) in Smart Cities, it is necessary to integrate the transport services with Hybrid System Intelligent Choices. To create an enhanced environment for traveling, to collect citizen-friendly options and to build attractive strategies for travel that should inter-dependently connect a person with his preferences in routes [18].

[15]By design, traditional path planning algorithms, such as Dijkstra and A*, are for static graphs and are not suitable for the dynamic, real-time traffic environment of urban road networks. In recent years, researchers have proposed hybrid systems to overcome this issue, which satisfy real-time dynamic path planning in urban settings. This hybrid system is an integration of different algorithms, such as the genetic and simulated annealing algorithms. The integration of Cyber–Physical Systems (CPS) and Internet of Things (IoT) technologies for smart cities could help to solve traffic-complication-related issues and significantly improve the overall mobility within the smart city. Among customs, hybrid services and systems can generate beneficial relationships with transportation modes, such as car sharing, bike sharing, taxi services, and so on. The integration of Auto-drive with IoT and the cloud helps intelligent coordination of Centralized algorithms. Such coordination can make the best use of traffic infrastructure management, including a set of performance-quality indicators, pavement condition, fuel savings, U-space services, and environmental feedback.

5.1. Overview of Computational Intelligence

On the trip to the development of the hierarchical hyper Heuristic (HH) for Dynamic Multi-Depot Vehicle Routing Problems (DMVRP), a simple genetic algorithm and some test instances were utilized, where a helicopter be utilized for rapid distribution of goods to the emergency and permanent stations of the paramedic system of Uruguay. This is not only and only the first experiment of hybridization of the results of the most distinct algorithms. Also, heuristics cover those who can be based on simple metrics, thermal exchange between Melbourne and the rural retreat of Yarram for the control of a cooling system, air conditioning by an energy-hungry data centre for greenhouse gases in order to improve its energy efficiency, harm the world enormously, provided a running contribution or in reverse, how the deployment of a vehicle network for the system of Western Australia surveillance of traffic and public safety has had a big impact on the operating costs of both displaced patrols and available vehicles. The interpolation is exclusive to one of the considered agents, generally treating the entire environment as immutable [3].

When road networks get involved in transportation, problem-solving procedures are usually utilized to identify the dynamic and the best paths through the consideration of frequently changed costs and traffic states. These problem-solving procedures can be divided into exact algorithms and heuristic/metaheuristic algorithms. The shortest path problem (SPP) is the first algorithm in which, connected with the Chicago Transportation Center motivated by an IEEE Intelligent Transportation Systems Challenge in 2002, the winners have utilized a worldwide changing heuristic algorithm. For an illustration, there are yet some detrimental trade-offs concerned with paths that are slightly better in terms of their length, but their smoothness is significantly uneven. To defeat such a state of affairs, they have resigned to jerky roads and such modification has permitted them to stay competitive also against the winners' path in the route competition called MobiAmI 2008 [28]. Considering the fact that these improvements are achieved in a direct search, they have quickly recognized the potential of soft computing methods, finally taking a decision for variation of this search of individuals' heuristic among the methods of genetic or ant-colony algorithms. The collaboration and possible cross-breeding of genetic algorithms and ant-colony methods, therefore relies on the results of on-going or finished work with identification of various routing problems, and also the general enhancement of traditional methods such as Dijkstra, heuristic, or A-star path searches. Vanity will be one of the enemies of those who read the rest of this article.

5.2. Types of Computational Intelligence Algorithms

Computational intelligence techniques are extensively applied in the route planning algorithms to enhance the services offered by the IVA networks. For instance, the attention mechanism and long short-term memory (LSTM) network are used to implement attention-based, interactive trajectory prediction for decision making, incorporating physical understanding and social conventions. Soft attention and hard attention are used to capture physical interactions and social interactions. Additionally, multimodal trajectory prediction is made by considering prediction uncertainty. This method outperforms the state-of-the-art Baseline LSTMs for one-step trajectory prediction models on the Argoverse motion forecasting benchmark. On the other hand, K-ethon Linear Temporal Regularizer (KLTR) and Decoder are used in a generative recurrent neural network-based trajectory prediction model for autonomous route planning. KLTR is used to encode class labels and the fact time step efficiently in an efficient way. The proposed trajectory prediction model is an end-to-end model that integrates features extraction, class prediction, temporal dependency, and stochastic generation [29]. On the other hand, progressive route planning architecture consists of two generative adversarial networks (GAN). Progressive Route Planning GAN (ProgRPGAN) is introduced for interactive autonomous navigation in real-world environments. Using both self-supervised and reinforcement learning, a generative model, ProgRPGAN, predicts natural, diverse, and efficient routes that take interactive behaviors into account. In the meantime, the discriminator, a low computational complexity architecture, distinguishes real routes from fake routes to iteratively improve the generative model. As compared to state-of-the-art dense, end-to-end navigation methods, ProgRPGAN is shown to make more admissible predictions, which yield more safe and human-friendly behaviors [30].

Dynamic route planning algorithms play an essential role in the effective operation of IoT (Internet of Things)-connected autonomous vehicle networks. In this section, the popularity of computational intelligence techniques applied for dynamic route planning in the field of IVA networking will be discussed in detail [6].

6. Case Studies and Applications

Urban traffic systems are becoming increasingly complex and require adaptive route planning in consideration of both traffic conditions and vehicle-network connectivity conditions [31]. An overall solution of the problem is presented in this paper, which consists of two main levels. We first introduce a system model and traffic simulation environment designed to consider the impact of IoV/C-ITS communication infrastructures on the transportation network and investigate more extensively the opportunities and challenges involved in dynamic vehicle routing. An original multi-attribute road and intersection metric is defined for specific road and intersection positions using a multi-agent process with minimum and maximum quantiles of the communication-specific QoS parameters, which are identification age, conference duration, and CCM validity time.

The focus of this paper is to develop an intelligent routing system, featuring adaptive dynamic path-planning, for support of safe and reliable commuting of Cooperative Automated (CA) vehicles together with traditional human-driven vehicles in the era of IoT (Internet of Things) [3]. Since both CA and traditional vehicles could exist simultaneously on the road, investigations on this set-up are of pragmaticallycloser interest. [32] summarizes the trajectory planning framework for the autonomous vehicle equipped with wireless data transfer needs according to the dynamic road information. An end-to-end data connection is established from a source CA to a destination CA through various communication points when the data transfer condition (under communication performance and energy sufficiency, etc.) is satisfied. By considering the unpredictability of road dynamics and the uncertainty of data transfer condition satisfaction, the problem is formulated as a Partially Observable Markov Decision Process (POMDP). For coping with the existing quadruple attention conflict of environment, data transfer, available energy, and the system's general performance, an asynchronous advantage actor-critic (A3C) algorithm is used to provide a decision-making scheme for the dynamic pathological trajectory planning.

6.1. Real-world Examples of Dynamic Route Planning in Autonomous Vehicles

When a connected and autonomous vehicle (CAV) moves with its communication range CH, it establishes a connected graph called the communication graph (CH). Dijkstra's algorithm with a communication cost function is popularly used for searching for the shortest path in such a graph. When all the CAVs start moving, the dynamic route planning problem becomes richer than the graph traversing problem at a micro-level. In this problem, the vehicles could perform see-first operations at intersections and refactoring operations in suboptimal routes. Keeping the trade-off between resource optimization and quality of service (QoS) in mind, these dynamic route planning problems are further modeled as multiobjective optimization problems and solved using algorithms like space division multiobjective shuffled frog-leaping algorithm (SDMOSFLA) [18]. To validate the proposed real-time approach, input data from the proposed referencing model is utilized to solve MTSR using different algorithms like ACO, genetic algorithm (GA), and PSO.

Connected Autonomous Vehicles (CAVs) require dynamic route planning to find an optimal path between the source and the target, while handling environment changes and congestion in real time [33]. The planning algorithm should be able to handle real-world situations such as variability in infrastructure and interference in vehicular communication [3]. Road accidents usually happen at intersections, therefore, dealing with intersections is important in dynamic route planning. Several surveys and tutorials have been conducted for network optimization using the Internet of Vehicles (IoV). The objectives of route planning are to find safer, viable, and timely routes. Safer paths are determined from a vehicular communication perspective, ensuring reliability in data transmission and minimizing accidents.

7. Future Trends and Research Directions

Ensuring the IoV remains resilient in challenging traffic scenarios is the overarching goal. Simplifying this goal means optimizing route planning and services. These can primarily be divided into two main applications. In the first case, the focus is on individual vehicles routing schemes. In a contrasting scenario, applications focus on the optimization of regional traffic operations. The research focuses on finding the optimal route, signaling the optimization of reaching the travel time. We have already divided the major scenarios concerned by the current research so far. First, it takes us through environmental vehicle scenarios scenario. After a case-analysis, the focus is on more advanced environmental vehicle scenarios with wonderful intelligent systems. While the focus of the data allocation issue is on the maintenance system (equipment-to-management) persistent connections, and in particular to promote the use of additional resources. During this work, we have specified the most preferred sort category in our case. Our main aim is to write through basic solutions already proposed in the literature [15]. Additionally, it has been shown that the same problem can be solved with more intelligent algorithms or make it proud of the negotiation scheme. Abstract: The transport systems for the continuous development and growth of sustainable development and economic prosperity are of great significance. Among the most important features that the data change has been introduced in transportation development.

Vehicles today use their modules to sense the environment and communicate with each other in real time [32]. They are gradually evolving into full autonomous systems. The next generation of Internet of Things (IoT) vehicle networks will provide more bandwidth than is currently possible. This future trend is characterized by directional propo-sals and vibrations. Vehicle transceivers can directly exchange download information. This can be used to assist the sensor as well as with map updates, where increased bandwidth can become more effective. Routes are not only optimal in terms of energy, time, and cost savings [5]. Future trends include the addition of new criteria that account for direct data transfer requirements. The fastest vehicle plans for the shortest path in terms of time and installs a filter to consider more advanced criteria.

7.1. Emerging Technologies in Autonomous Vehicles

The concepts related to autonomous and connected vehicles contrast systems that have already been developed and implemented (e.g., the IEEE 802.11p standard and centralized traffic control centers) and popular models in which vehicles communicate directly with each other using the VANET (Vehicular Ad-Hoc Network) concept. The main goal of existing vehicle communication systems is to ensure that vehicles report themselves to others through the exchange of information such as fuel level, the level of pollution emitted, or time before turning. However, the information exchange takes place exclusively between vehicles, while the proposed approach assumes the existence of a vertical infrastructure, which ensures the transmission of data received from vehicles to an Azure cloud in real-time. As the authors write, in practice, the quality of information contained in the real-time data stream gathered from the road infrastructure with sensors is not known [34].

Emerging technologies in the field of Internet of Things (IoT) are enabling the transformation of transportation systems through the use of autonomous and connected autonomous vehicles (CAVs), laying the groundwork for the development of route planning algorithms. Although the technologies being leveraged for this purpose span various disciplines and a plethora of IoT sensors and big data, the three driving recent developments in CAV networks are big data, AI, and IoT [35]. The integration of CAVs and IoV essentially facilitates the development of dynamic journey planning algorithms for CAVs based on inputs from the IoT and on data analytics such as AI. This integration has the potential to revolutionize transportation systems and devices, reinforcing both safety and comfort [36].

8. Conclusion and Key Findings

In future work, although involving ANN, and fuzzy-set theory, CI may find the capability to in particular operate optimally with a dynamically-overlapping-environment IoV. To investigate to what extend the (not mis-managed) purse of driver or the auto-pilotly-conducted by electric-car-wife speech user can feel comfortable to practice CI with real-time global and local information is an alternative topic that shall be discusses in our next paper. The communication-ability-conversions in the case of dependency on LTE, VANET, RSU and roadside sensor even in providing comfort feeling to passengers, families and drivers is another possible topic. Digital Wristband-Internet of Vehicles is another fresh approach to be brought in the framework of the most updated EMH that shall be counsel. We also recognize that, in the domain of IoT it is essential to create a dynamic route optimization methodology designed to manage vehicles with different traffic preferences for navigating the IoV.

In fact, although until now, the term CI did not accurately specify a single perspective but AI, in the context of this review the term has a narrower definition encompassing ANN, fuzzy set, GA, PSO, and rough set theories. The scope here is to create awareness and inspire those in the profession to tailor CI for dynamic route finding where (or whenever) CI connects IoV networks by ensuring the anticipated level of end-user perceived quality of routing applications. We have demonstrated that although CI has several alternative names and expressions, it is identified to be a mature planner, suitable for hands-free integrating with real-time traffic, social events, and road sensor or VANET viewing components of IoV. The road-sensor-viewing system is demonstrated further by introducing the artificial-intelligence theory labelled PrecautionMatching, which is an ANP-MOF method and feature-selection approach. Then, the system will decide to generate paths according to vehicle-sensed real-life conditions]. For instance, considering [Management That Fixes, Trains, Enhances and Cancels]. After characterising the contribution of practical safety throughout these road sensors, CI is capable of once fitting lower-energy-car owners need to handle defective parts.

In this article, we provided an overview of the use of computational intelligence in intelligent transportation systems, focusing on computational intelligence in static route planning, followed by a critical view on the challenges and constraints in adopting computational intelligence for dynamic route planning in future smart cities. The review discusses the use of computational intelligence in dynamic route planning from three different perspectives—route planning for connected and autonomous vehicles, routing relying on vehicular ad hoc network- (VANET-) based communication, and routing needing only cellular communication facilities. This discussion is followed by the discussion of the use of computational intelligence for alternative modes of future smart city transportation, including cycling and walking in implementing network routing and route planning across a smart city.

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