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Research on AI-Powered Smart Cities for On-Demand Autonomous Vehicle Automation Systems

QI LE[1], DR NOOR ALIA BT AWANG[2 a], DR MUKIL ALAGIRISAMY[3 b]

[1]PhD Research Scholar in Engineering, Lincoln University College Malaysia

[2,3] Professors in Lincoln University College Malaysia

Contact Details: [a]nooralia@lincoln.edu.my, [b] mukil@lincoln.edu.my

Abstract

Automated "vehicles (AVs) have the potential to positively affect transportation and smart cities in many ways. Vehicle platooning, in which one automobile follows closely after another, might benefit from AV technology, which could reduce the amount of space between vehicles. However, well-made AVs have the potential to have a far larger impact [27]. Currently designed roads and highways will need to be modified when autonomous vehicles (AVs) gain popularity [14]. We need to start planning now to make the most of AVs' potential in smart transportation networks. Researching and capitalising on the distinctive features of AVs holds great promise for advancing technology and creating AV systems with various additional advantages. This is because there are "the following three major categories of research topics: Traffic data management including autonomous vehicles and road infrastructure [15].

Vehicle-to-grid "use cases for autonomous vehicles (V2G). A battery is a typical source of energy for AVs. When there is a mismatch between supply and demand in a smart grid, electricity production prices might go up [16]. One solution is to leverage the enormous battery capacity of AVs to maintain and balance the power grid. If the amount of energy produced exceeds the amount of energy needed, we may utilise the surplus to charge the AVs. Similarly, we may discharge the AVs to deliver extra power to the grid if demand exceeds supply [26]. Parking garages equipped for vehicle-to-grid services were made available to AVs through a centralised scheduling system. To solve the ILP version of the coordinated parking problem [17], we shall employ a decentralised approach. However, V2G services are limited in their adaptability since AVs are confined to a single parking location. Only by counting automobiles can V2G services be recognised, but this issue also has to account for the power exchanged and voltage effect caused by these vehicles. Therefore, the actual power flow of AVs must be considered while scheduling charging periods. As a result, figuring out parking spots for autonomous vehicles is crucial for both vehicle-to-vehicle and vehicle-to-pedestrian interactions "rebalancing, and it's an important field to research [18].

Keyword: Automated Vehicles, Smart Transportation Network

INTRODUCTION

A contemporary smart city's effective intelligent transportation system is essential for a wide range of human activities and for the provision of social advantages. It is expected that the Autonomous Vehicle (AV) will transform the transportation system in the future. Many modern AV systems may be implemented in transportation and smart grids thanks to the completely automated AV navigation and cutting-edge [1] Artificial Intelligence (AI) technology. First, we'll look at the present transit options and analyse their limitations. After that, we'll get to the heart of the matter: on-demand transportation system using AVs powered by AI technologies [2].

While individual AVs develop and implement completely automated control, group control can bring extra benefits and potentials. AmoD (Autonomous Mobile Deployment) has been presented as a new transport mode that uses autonomous cars as the transportation service carriers and offers a wider range of services. This year, a real-world AMoD, dubbed "Waymo One," was established to provide commercial autonomous vehicle service in Phoenix, AZ, USA, where a customer may request pickup via a smartphone app. The Autonomous Vehicle Public Transportation System (AVPTS)[3] is an example of a public transportation system that uses AVs to facilitate ridesharing in order to save money. In order to determine the best routes and timetables for clients, a control centre oversees a fleet of AVs. Maximizing profit is another benefit of this system [4].

LITERATURE REVIEW

Humans have been innovating in the field of transportation for thousands of years, from animal-powered vehicles to modern trains and automobiles [5]. There has always been an emphasis on improving transportation efficiency and safety while also cutting down on travel time and expense. Among today's most prevalent modes of public transportation, taxis, buses, and subways are the most prominent. People choose different modes of transportation based on their own requirements, and each has its own set of perks and cons. Public transportation like buses and subways, on the other hand, can accommodate a large number of passengers at a minimal cost and almost always run on time [6]. A large number of customers may necessitate crowding, and the service provider may only stop at popular spots, which may not be the actual origin or destination for a single passenger. Taxis, on the other hand, may provide a point-to-point service that is comfortable for the passenger and eliminates the need for them to share space with random individuals. Passengers may hop on and off at the beginning and end of their journey without having to make a detour. Cab fares are often more expensive than those of the bus and metro, and in densely populated areas, customers may have to wait a long time to acquire a taxi. Traffic congestion may be exacerbated by a lack of taxis in the area. Mobility on Demand (MoD), such as Uber and Lyft, has arisen in recent years, allowing customers to actively make trip requests to define their pickup and dropoff locations [7, 8]. At the given times and locations, drivers will pick up passengers on demand.

Autonomous cars have been hailed as the next big thing in transportation (AVs). AVs are autonomous cars that can drive on their own without the active control of human drivers on the road. Sensors and communication units allow them to gather information about the physical world for completely autonomous control, such as lane changes and merging manoeuvres [9]. We may predict that most AVs will be powered by an electric battery based on current industry developments. Since the 2007 Defence Advanced Research Projects Agency (DARPA) Urban Challenge, it has garnered great interest [10]. They accomplished approximately 3 million miles of self-driving on public roads by May 2017 after successfully demonstrating that their AVs were capable of doing so in 2015. Tesla has made autopilot available on business cars that are capable of self-driving functionality in its most advanced form. It is clear from the examples above that AV is a technology that will become more widespread in the near future [11].

STATEMENT OF THE PROBLEM

Predicting travel demand for a certain area A and a specific time period T is our goal, and the time period T is divided into equal halves by m n grid cells. The time between each interval is measured in microseconds, with a typical value of τ g. All requests for travel from a grid cell (i, j) ∈ A in the time interval t ∈ T are counted as a single request for travel. In addition to using past data, other metadata like day, time, and weather may have an impact on the forecast of future travel demand. For example, during the peak hours of business on weekdays, demand is likely to be higher. In this way, they might be taken into account to enhance the forecast if desired. The objective is to predict the demand of each grid cell $(i, j) \in A$ for the future $\tau \geq 1$ interval. Suppose we are in the T_c the interval. We predict the travel demands, $\hat{\Theta} = \{\theta^{Tc+1}, \theta^{Tc+\tau}, \forall\ (I, j) \in A\}$, based on the his topical travel demand $\Theta = \{\theta^t, \forall\ (i, j) \in A, t \in 1,2,...,T_c\}$ and other optional metadata [12, 13].

Objective of the Study

- To explore the Dynamic Lane Reversal-Traffic Scheduling Management Scheme for AVs

RESEARCH QUESTIONS

- What is the procedure for AVs to avail dynamic lane reversal-traffic scheduling management?

Research Methodology

This section explains the algorithm used to solve the problem. It has three parts: MPC, GA, and solvers. Figure 1 depicts the algorithm's flow. Based on MPC, we use present and predicted information to optimise a finite time horizon, and then iteratively enhance the solution with new information available in the following time interval [19]. Travel demand forecasters can get more accurate predictions by incorporating the most recent data available in each time period under this MPC paradigm. At the beginning of each interval of time t, we first update the requested information R and R. GA and solver portions get the revised data.

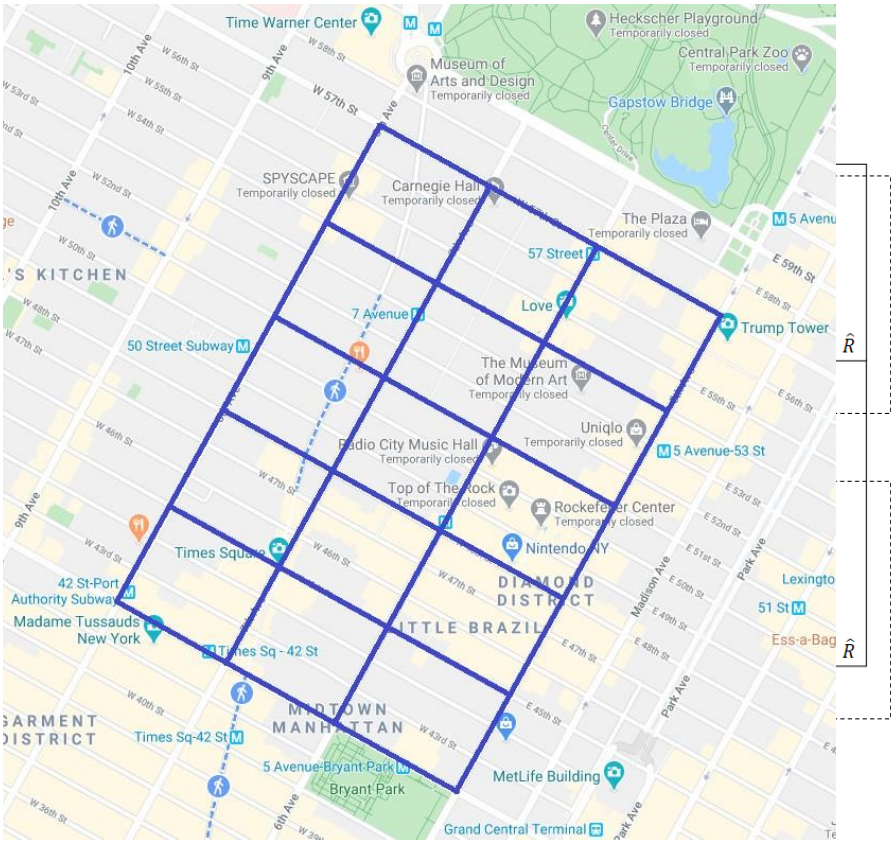

Figure 1 Algorithm Flow Chart

Research Design

New York City Open Data yellow cab trip data will be used to test the efficiency of the system and the suggested strategy. Data gathered during trips will be used to create a transportation request pool. New York City, as seen in Fig. 2, is chosen to represent the road network since it has a large number of vertices and edges. Connecting road segments of the same length are represented by 4 X 6 vertices. If all vehicles drive at a constant speed, then cij is equal to one time slot for all edges with the same distances. Running across each edge is supposed to take the same amount of time. On top of that, we disregard traffic control signals like stop signs and flashing red and green lights. Qualified vehicle capacity (Q_k) and passenger capacity (q_r) are both set at 5 in this case [20].

The set of transportation requests R and predicted travel demand $\hat{R}$ are randomly selected for the initial time interval from the transport request pool. Since $\hat{R}$ is the prediction of future R^J in the next time interval, we build their correlation by randomly sampling requests from $\hat{R}$ to form R^J. THIS sampling can simulate the imperfect prediction of $\hat{R}$ since $\hat{R}$ may not appear as new requests in later time intervals. New requests will be added to a later $\hat{R}^J$ to maintain its value. Any served requests will also be removed from the set of requests.

Figure 2 The selected road network

DATA ANALYSIS

For the purpose of "It takes a lot of training time for our proposed TSC method to update the Q-parameters. network's the rate of convergence is a major issue during the training phase [22]. When it comes to putting TSC's deep RL algorithms into practise, programming languages like Python and Tensor flow are employed. The Open AI Gym has two simulated environments, SUMO and Sumo-web3d. The GeForce GTX 1080 Ti "does all the tests for us.

CONCLUSION

The "In this thesis, we suggest a novel autonomous vehicle (AV) system for the smart cities of the future, called AVoD. The major focus of AVoD is on AI-based transportation systems that include AVs. By making better use of their independence, autonomous vehicles (AVs) may contribute to the betterment of transportation and of society as a whole. Three of the most important methods are the forecasting of traffic data, the management of autonomous vehicles, and the adaptation of road infrastructure [23]. The fundamental objective of this research is to improve the AV transportation system via the application of artificial intelligence (AI). We provide AVoD solutions to increase the usefulness of autonomous cars due to their complete independence and fast reaction time. Predicting traffic patterns, supervising the deployment of autonomous vehicles, and adjusting to new circumstances all require a great deal of data "development, maintenance, and expansion of road networks are three of the most significant contributions to transportation networks [24].

LIMITATIONS OF THE STUDY

Our deterministic issue may be transformed into a stochastic or resilient optimization problem. The stochastic or robust formulation may loosen the constant speed assumption since it enables flexibility in the vehicle's speed and location. In the actual world, there is a lot of unpredictability on the roadways, such as traffic jams and accidents. There are a lot of simulations used in this thesis. Simulating and fine-tuning the agent's settings in a virtual environment is ineffective. When it comes time to put our trained agents and systems into action, we'll look into it. In addition, safety is the most important factor when designing a real-world system. The system should contain additional safety precautions. For example, the wording of the problem can enforce a safety gap between any two cars.

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