Multi-Class Fleet Management for Autonomous Mobility-on-Demand Service

Semester 8 Project Thesis

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February 2, 2020

Candidate's Declaration

We declare that the project work titled "Multi-Class Fleet Management for Mobility-on-Demand Service" done at Singapore University of Technology and Design and submitted at Indian Institute of Information Technology, Allahabad is the bonafide work of Niharika Shrivastava(IIT2016501). It is a genuine record of our study carried out from January 2020 till present under the guidance of Prof. Malika Meghjani and Prof O.P. Vyas. Due acknowledgements have been made in the text to all the materials used.

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Abstract

Recent developments in Mobility-on-Demand (MoD) systems have demonstrated the potential of road vehicles as an efficient mode of urban transportation. This paper addresses the problem of routing, ride-sharing and re-balancing a multi-class fleet of heterogeneous vehicles providing autonomous (i.e. self-driving) mobility on-demand service. We provide a chain of transportation with three classes of autonomous vehicles including cars, buggies, and scooter. Each class of vehicle can access a subset of the network, such that, there are some links exclusive for that particular class. Vehicles are assigned to passengers based on parameters such as travel time, passenger pick-up and drop-off. Each assignment may consist of a set of vehicles allocated for one trip that is composed of multiple legs served by different vehicles. For example, first mile pick-up on a scooter, middle mile in a car, and last mile in a buggy. We also aim to provide optimal transit points for this service within a capacity-bound transportation network, where congestion might disrupt throughput.

Contents

1 Introduction

1.1 Autonomous Mobility-on-Demand Systems

Autonomous (i.e. robotic, self-driving) vehicles are rapidly becoming a reality and hold great promise for increasing safety and enhancing mobility for those unable or unwilling to drive [1]. A particularly attractive operational paradigm involves coordinating a fleet of autonomous vehicles to provide on-demand service to customers, also called autonomous mobility-on-demand (AMoD). AMoD systems provide demand-responsive transportation services using self-driving vehicles. These vehicles generally cover partial to complete journeys of the passengers, depending upon the vehicle accessibility to the road network. An AMoD system may reduce the cost of travel [2] as well as provide additional sustainability benefits such as increased overall vehicle utilization, reduced demand for urban parking infrastructure, and reduced pollution (with electric vehicles) [1]. The key benefits of AMoD are realized through vehicle sharing, where each vehicle, after servicing a customer, drives itself to the location of the next customer or rebalances itself throughout the city in anticipation of future customer demand [3].

1.2 Congestion Management

In terms of traffic congestion there has been no consensus on whether autonomous vehicles in general, and AMoD systems in particular, will ultimately be beneficial or detrimental. It has been argued that by having faster reaction times, autonomous vehicles may be able to drive faster and follow other vehicles at closer distances without compromising safety, thereby effectively increasing the capacity of a road and reducing congestion [4]. On the downside, the process of vehicle rebalancing (empty vehicle trips) increases the total number of vehicles on the road (assuming the number of vehicles with customers stays the same) thereby leading to congestion [5, 6]. These statements, however, do not take into account that in an AMoD system the operator has control over the actions (destination and routes) of the vehicles, and may route vehicles intelligently to avoid increasing congestion or perhaps even decrease it.

1.3 Multi-Class Fleet Sizing

Our fleet of multi-class vehicles [7] range from slow-drive, easily navigable personal mobility scooters for individuals, to medium speed autonomous buggies and faster speed self-driving cars with larger capacity and accessibility to larger lanes and main streets. The car is most ideal for travel along the road network, as it has the highest speed and is capable of longest range. However, the scooter would be more ideal for narrow passage ways and crowded pedestrian environments. It is the cheapest platform, most efficient in terms of weight, most maneuverable (smallest turning radius), and small enough to fit inside building hallways and on small sidewalks. The buggies are most well suited for large pedestrian areas, such as parks, plazas, airport terminals and hospitals [Fig. 1].

Fig. 1. SMART's multi-class autonomous vehicles: road car (upper left), buggy (lower left), scooter (right).

By using all three classes in combination, a greater accessibility and service coverage can be achieved such that the users can be taken not just between building pick-up and drop-off points, but even from the room of one building to a specific room in another building several kilometers away. It is best applicable to elderly or disabled people who might need assisted modes of navigation.

1.4 Ride-Sharing in MoD systems

Ride sharing services, such as UberPool and Lyft Line, are transforming urban mobility by providing timely and convenient transportation to anybody, anywhere, and anytime. Also known as vehicle pooling options, these systems allow several passengers, to share a vehicle when traveling along similar routes. Similar services include Via, which provides vehicle pooling with vans, and Bridj, which provides an alternative to buses. Currently these companies relay on drivers to operate the vehicles.

One of the major inefficiencies of current MoD systems is their capacity limitation, typically restricted to two passengers. [8] showed that up to 80% of the taxi trips in Manhattan could be shared by two riders, with an increase in the travel time of a few minutes. Much of the fleet management literature for MoD systems considers the case of ride-sharing without quantifying the benefits of larger-scale ride pooling, focusing on fluid approximations [3], queuing based formulations [9], case studies in specific regions [e.g., Singapore [2]], and operational considerations for fleet managers [10]. The ride-pooling problem is related to the vehicle-routing problem and the dynamic pickup and delivery problem [11, 12, 13, 14, 15], where distributed demand must be picked up and delivered within specified time windows.

1.5 Re-balancing of Network

Besides the computation of efficient vehicle schedules in an AMoD system, the proactive relocation of idle vehicles can have a significant influence on the fleet performance. Since the demand for vehicles is often not uniformly distributed, vehicles tend to build up in regions of low demand while vehicles are depleted in regions of high demand. This mismatch in vehicle supply and demand means that vehicles often have to travel further than necessary to pick up customers, which leads to higher waiting times and more customer walkaways. It also means that the number of passengers which a fleet can transport in a given time is less than optimal. Vehicle re-balancing focuses on positioning the idle vehicles so that future demand can be served with increased efficiency.

2 Literature Review

- In [8], a large-scale study highlighted some of the benefits of car pooling but was limited to static routes with two riders per vehicle (optimally) or three (with heuristics). In [16] they present a more general mathematical model for real-time high-capacity ride-sharing that (i) scales to large numbers of passengers and trips and (ii) dynamically generates optimal routes with respect to online demand and vehicle locations. They consider ride-sharing with rider capacity of up to 10 simultaneous passengers per vehicle. They also incorporate re-balancing of idling vehicles to areas of high demand. Under the assumption of one person per ride, [16] shows that 98% of the taxi rides currently served by over 13,000 taxis could be served with just 3,000 taxis of capacity four. If a maximum delay of 5 min or more is allowed, higher-capacity vehicles (i) increase the service rate significantly, (ii) reduce the waiting time, and (iii) reduce the distance traveled by each vehicle. In serving 100% requests, the computational complexity reaches exponential.

- The methods in [17] builds on the works of [16]. Based on historical data, [17] computes a probability distribution over future demand of passenger requests, samples from which are incorporated into the decoupled algorithm in [16]. The predictions improved the positioning of the vehicles towards satisfying future requests (service rate for requests reached 100%), reducing waiting time (1 min) and travel time (1.5 min). This also increased the distance traveled by each vehicle and was computationally more expensive due to increased service rate. While computing the predictions of future requests, they also did not account for seasonal changes or online adaptation.

- [18] presented a network flow model of an AMoD system on a capacitated road network, proving that it is always possible to route re-balancing vehicles in a coordinated way that does not increase traffic congestion. They used an A* approach using the Bureau of Public Roads heuristic [19] to create a congestion-aware vehicle routing algorithm. However, the study did not include stochastic information (e.g., demand prediction, travel time uncertainty) for routing and re-balancing problem, as well as a richer set of performance metrics and constraints (e.g., time windows to pick up customers).

- In [20], the fleet operating area is optimally partitioned into re-balancing regions. Real-time demand estimate for every region is determined using incoming requests based on which idle vehicles are optimally assigned to these regions. The service rate was 99.8% of taxi requests in Manhattan using 3000 vehicles with an average waiting time of 57.4 seconds and an average in-car delay of 13.7 seconds. There was a reduction in the average travel delay by 86%, the average waiting time by 37%, and the amount of ignored requests by 95% compared to [16] at the expense of an increased distance travelled by the fleet . The algorithm could not utilize fleets with varying vehicle capacities and incorporate the existing public transportation infrastructure.

- In [21], a method is presented to optimize the vehicle distributions and fleet sizes for MoD systems that allows requests to share vehicles. It determines how many vehicles are needed, where they should be initialized, and how they should be routed to service all the travel demand for a given period of time. There was a reduction in the fleet size by 69% by allowing up to two passengers per vehicle and by 77% for up to four passengers per vehicle while guaranteeing all travel requests are serviced compared to the baseline. There was a travel delay of 1.7 mins and 2.8 mins and waiting times of 35.4 secs and 41.9 secs for vehicle capacities of two and four respectively. However, there was no lower bound on fleet size required for 100% service rate. [21] is computationally expensive for online adaptation.

- In [7], genetic algorithm was applied to the multi-class fleet sizing and vehicle assignment problem providing AMoD service using a fleet of heterogeneous vehicles (cars, buggies, scooter, walking). Each assignment may consist of a set of vehicles allocated for one trip that is composed of multiple-legs served by different vehicles. The lowest total travel time per passenger was evaluated to be 376.982 s using 342 cars, 68 buggies and 302 scooters. However, The total cost of vehicles (budget) varies exponentially (inversely proportional) with respect to the total travel time per passenger. Moreover, when the demand is much greater than the expected demand used to optimize the fleet size, the total average travel time for multi-class is worse than single-class.

3 Proposed Methodology

3.1 Timeline

Timeline	**Tasks**
15 - 31 January	Study the previous work on fleet sizing, assignment and re-balancing
1 - 14 February	Build a road network from existing opensource GIS (e.g. open street maps)
15 - 29 February	Develop tools for querying APIs for public transport schedules and travel times
1 - 14 March	Integrate existing tools for graph queries and path planning algorithms
15 March - 30 June	Develop novel algorithms for multi-class fleet assignment and re-balancing

3.2 Method Overview

4 Requirements

4.1 Data set

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4.2 Hardware Requirements

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4.3 Software Requirements

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5 Implementation

6 Results

7 Conclusion

8 Future Scope

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