Scaling Urban Mobility Transformation: Ride-Sharing Meets Mass Transit

Danushka Edirimanna[a*], Hins Hu[a], Samitha Samaranayake[b]

[a] Department of Systems Engineering, Cornell University, Ithaca, USA
ke233@cornell.edu, zh223@cornell.edu

[b] School of Civil and Environmental Engineering, Cornell University, Ithaca, USA
samitha@cornell.edu

[*] Corresponding author

Extended abstract submitted for presentation at the Conference in Emerging Technologies in Transportation Systems (TRC-30)
September 02-03, 2024, Crete, Greece

April 29, 2024

Keywords: transportation, multi-modal transit, demand-responsive mobility

1 Introduction

The rise of technology-driven ride-hailing services like Uber and Lyft has revolutionized urban mobility, overshadowing traditional taxi services and diminishing personal vehicle ownership. In cities like New York City, ride-hailing services now complete over 600,000 trips per day as of February 2024. While ride-hailing offers passengers convenient and reliable service, they have also been associated with negative externalities. Recent studies indicate that ride-hailing services can amplify the total vehicle miles traveled (VMT) on road networks compared to personal vehicle trips, primarily due to deadheading, resulting in heightened congestion while simultaneously decreasing transit usage. Diao & Kong (2021).

Mass transit systems, characterized by their ability to transport passengers more efficiently through the utilization of higher-capacity vehicles, excel these ride-hailing services primarily in areas with dense demand Aftabuzzaman *et al.* (2010). However, they often confront the challenge of inadequate coverage for the first and last mile of a trip. To mitigate this challenge, passengers often resort to complementary modes of transportation such as ride-hailing and bike-sharing to bridge the gap to mass transit. (Shaheen & Chan (2016), Huang *et al.* (2021)).

Recently, several studies have explored the potential advantages of integrating ride-sharing and ride-pooling services with mass transit networks. Salazar *et al.* (2020) showed that the coordination between ride-hailing fleets and mass transit in New York City could yield reductions in both travel times and emissions. Computational study by Stiglic *et al.* (2018) that integration of transit with ride-pooling can enhance the overall service rate while concurrently increasing transit ridership.

In this paper, we envision a transit-integrated ride-sharing system wherein passengers utilize ride-sharing vehicles to connect with mass transit. The operation of such system involves selecting travel options for passenger, allocating passengers to appropriate mass transit services, assigning passengers to vehicles, and planning routes for ride-sharing vehicles. Moreover, these decisions need to be made promptly in real-time. We define the operational problem as the transit-integrated ride-sharing (TIRS) problem and provide an algorithmic framework for operational optimization. Furthermore, we simulate an integrated system within the city of Chicago using our proposed framework to quantify benefits and validate its scalability.

2 Problem Description

Passenger requests arrive dynamically in real-time and are aggregated into batches, typically occurring at intervals such as every 30 seconds. Once a batch is collected, the transit-integrated ride-sharing (TIRS) problem is solved. The problem assumes the following inputs: 1) a transit schedule (e.g., described by General Transit Feed Specification (GTFS)), 2) a batch of passenger requests (described by origin, destination, and pick-up and drop-off time windows), and 3) the current state of the ride-sharing fleet (including current location and planned route). The vehicles can be dynamically rerouted to serve additional passengers as long as capacity is available and quality of service constraints are not violated for existing passengers.

The system serve the passenger with one of the following option.

1. **Multi-modal option:** The trip consists of three segments: 1) the first-mile, 2) the transit-leg, and 3) the last-mile. The first and last miles represent the passenger's journey to and from the transit stops facilitated by a ride-sharing vehicle. If either the first or last mile segment is very short, we assume the passenger will walk to or from the transit stops.

2. **Ride-sharing option:** The request is entirely served by a ride-sharing vehicle.

The primary objective of the optimization problem is to fulfill as many requests as possible, with the secondary objective being the minimization of the total vehicle miles traveled (VMT) added to the ride-sharing fleet. Note that the objective could also encompass other metrics, such as quality of service constraints. The travel time for all vehicles is assumed to be deterministic.

3 The Trip-Vehicle Assignment Model

The solution framework consists of 3 components: 1) Identify transit legs for multi-modal options, 2) Calculate routes and costs for serving ride-sharing segments, 3) Assign passengers to trip options and ride-sharing vehicles.

There is a large number of transit-leg options to consider for a given passenger request. This is attributed to two factors: 1) the multitude of transit lines and vehicles operating simultaneously in major cities, and 2) numerous combinations of departure and arrival stops for a given transit line. For instance, in the city of Chicago, there are 67 million such transit leg options. However, this extensive list can be pruned through feasibility checks and heuristics. Tight quality of service constraints render many transit legs infeasible due to extended waiting times and detours. As a heuristic approach, we assume that passengers connect to a transit line at the closest stops from their origin and destination, as this minimizes the first and last mile distances and consequently is more likely to add fewer miles to the ride-sharing fleet.

We identify the first/last mile segments for the calculated transit-legs. Each such segment is described by 1) the origin and the destination of the segment, 2) earliest pick up time, 3) latest drop off time. Similarly, the journey for ride-sharing options can be described with the same attributes. We pool all the ride-sharing segments. For each pair of ride-sharing segment and ride-sharing vehicle, we calculate routes and relevant costs for serving the segment. The cost represents the additional number of miles the vehicle must travel to serve the segment. Note that, not all such pairs produces feasible paths. Each route calculation involves solving a small instance of vehicle routing problem as there can be passengers already on board of the vehicle and/or assigned to be picked-up from previous iterations.

Finally, we formulate the assignment problem as an Integer Linear Problem (ILP), which can be efficiently solved using a commercial solver due to the decomposition of the routing and assignment problems. The ILP comprises three types of constraints: 1) a vehicle can be assigned to at most one ride-sharing segment, 2) if a request is served with the ride-sharing option, a vehicle should be assigned to serve it, and 3) if a request is served with a multi-modal option,

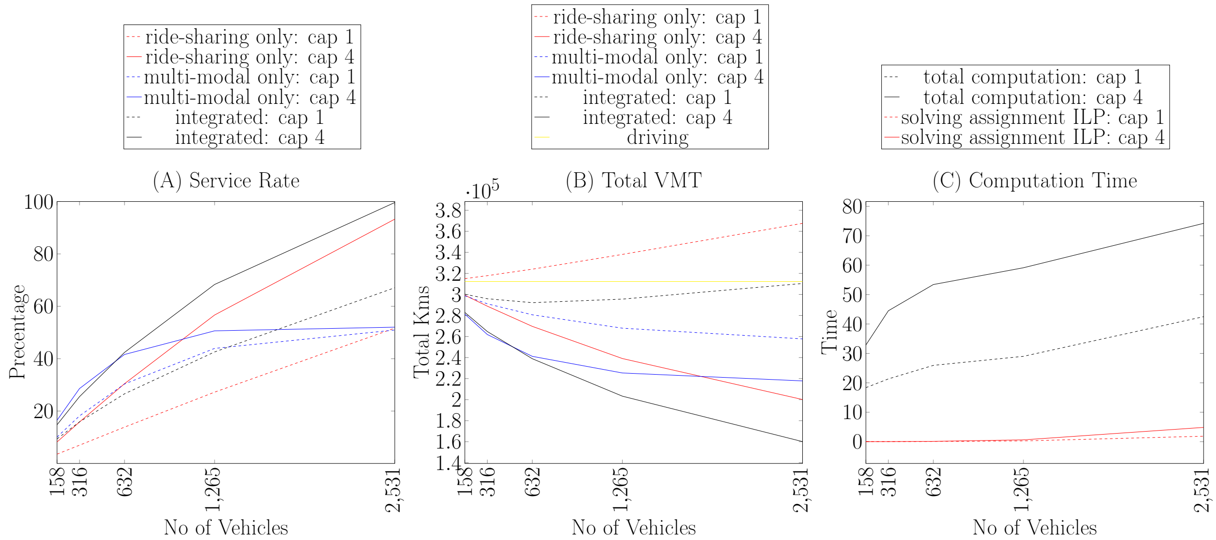

Figure 1 – *Service rate, Total Vehicle Miles Travelled (In KMs), and Computation Time (per minute) for varying vehicle capacities (1 and 4) and fleet sizes (185, 316, 632, 1265, and 2531).*

vehicles should be assigned for both the first and last legs (if required). The objective function includes a penalty for failing to serve a request and the summation of all the miles added to serve the selected ride-sharing segment with the selected vehicle.

4 Experiments

We generate commuter trips using the LEHD Origin-Destination Employment Statistics data published by the United States Census Bureau. The dataset contains home-work locations of employees. We only select trips that are longer than 3km as shorter trips are less suitable for multi-modal travel. Commuter trips headed to work are uniformly distributed between 6 am and 8 am, while return trips are distributed between 4 pm and 6 pm. These trips are generated within a circular region centered around downtown Chicago, with a radius of 16km. To expedite the experiments, a 10% data sample (63,283 requests) is utilized while maintaining data consistency across multiple settings. The transit system schedule is extracted from the GTFS data published by Chicago Transit Authority. Our framework is implemented in Python (3.9.7), and experiments are conducted on a Linux Server equipped with an Intel(R) Xeon(R) Gold 6244 CPU and 200 GB of memory. We utilize the Gurobi Optimizer (9.5.1) to solve the assignment ILP.

We allocate a time window of 20 minutes plus 20% of the shortest path travel time to fulfill a request from its origin to its destination. The additional 20% accounts for potential detours during multi-modal and ride-sharing options. This constant added time is designed to accommodate waiting periods for buses or ride-sharing vehicles.

To quantify the benefits of the integrated system, we simulate the system 1) serving requests with only ride-sharing option, 2) serving requests only with the multi-modal option, and 3) serving requests with both options (fully-integrated).

5 Discussion

Figure 1 (A) displays the average computational time required to solve commuter requests arrived in one minute. The framework can solve the TIRS problem in under one minute for all configurations, except for the highest number of ride-sharing vehicles, where it extends slightly by an extra 14 seconds. However, the results shows less than 5% of the computation time is devoted to solving the ILP. The remaining parts of the framework (i.e. generating transit-legs and calculating routes) can be executed in parallel. Therefore, the computation time can be reduced by allocating more parallel computing power to achieve real-time response. Moreover, we observe that the computation time scale linearly with the the number of ride-sharing vehicles.

In Part (B) of Figure 1, the resultant service rates for each setting are depicted. Notably, the integrated system consistently outperforms the service rates achieved by the ride-sharing-only system across all configurations. Substantial improvements of up to 15.35% and 12% are evident for capacity 1 and 4, respectively. Importantly, for capacity 4, the integrated system delivers the highest gains with a smaller vehicle fleet size of 632 (10 vehicles per 1000 requests), indicating significant improvements can be achieved with a smaller investment. Initially, at smaller fleet sizes, the multi-modal-only setting modestly outperforms both other approaches. However, the service rate quickly reaches saturation as the system exhausts passenger requests with feasible multi-modal options.

Figure 1 (C) shows the total vehicle miles traveled (VMT) by the ride-sharing fleet under the proposed integrated system. We assume that passengers who are not served by the system commute using private vehicles. We add their mileage to the total. The Yellow line represents the base case where everyone drives. Ride-sharing with capacity 1 performs worse than everyone driving, mainly due to deadheading, making it the least efficient. The performance of the multi-modal-only approach is similar to the service rate; it outperforms other approaches with small fleets, but the improvement saturates rapidly with the growing fleet size. However, a small fleet of 316 (5 vehicles/1000 requests) vehicles can reduce 47,554 km (15.2% of VMT) in the multi-modal-only setup. The integrated approach achieves higher service rates with reduced VMT compared to the ride-sharing-only setup. The integrated system can save of up to 48.7% (152,222 km) of VMT which could scale up to 1.52 million kilometers with 100% of requests.

6 Acknowledgment

This research is partially sponsored by the National Science Foundation under the grant CNS-1952011.

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