Modeling and Managing Operations of Mixed Human-driven and Autonomous Ride-sourcing Fleets

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Extended abstract submitted for presentation at the 11th Triennial Symposium on Transportation Analysis conference (TRISTAN XI)
June 19-25, 2022, Mauritius Island

January 12, 2022

Keywords: Dynamic modeling, MPC optimization, Simulation, Pricing

1 INTRODUCTION

As the autonomous vehicle (AV) technology attracts more interests in both industry and academia, it brings a vast set of new solutions and questions alike. One of the issues is the management of such an automated fleet, especially in the presence of traditional human-driven vehicles (HVs). The AV management problem includes many areas worth exploring, ranging from motion control to network design, detection technology to economic evaluation. In this paper, we study the modeling and control of AVs in ride-sourcing systems.

The modeling and control problem is complicated, involving stochastic behaviors of existing market users. The labor supply may exhibit different behaviors based on wage changes, adhering the income-targeting theory (Camerer *et al.*, 1997) or the neoclassical theory (Farber, 2015). Besides the labor supply, passengers also demonstrate varying behaviors. Wang *et al.* (2020) studies the order cancellation and its impact on a ride-sourcing system. Hörl *et al.* (2019) has designed operational plans for AV fleets based on such behavioral assumptions. These works mostly focus on pre-defined vehicle routing and order dispatching policies, rather than dynamic controls in real time. It is shown that a non-equilibrium dynamic pricing control scheme can bring significant benefits to the ride-sourcing operator (Nourinejad & Ramezani, 2020).

This work focuses on the fleet size and price structure for ride-sourcing services by a mixed fleet composition. A network simulation is developed to replicate individual behaviors and interactions in a ride-sourcing market, considering various personal traits and preferences. A dynamic control method utilizing a model predictive control (MPC) scheme is proposed to optimize the dynamic trip fares, driver wages, and AV fleet activation/deactivation in real time.

2 METHODOLOGY

2.1 Detailed Simulation Plant

A simulation environment is constructed to implement and test the proposed control method. The simulation provides flexibility in regard to behaviors of individual agents, i.e. passengers, drivers, and AVs. A static network map is also configured to replicate their path-finding and matching processes in an urban ride-sourcing environment.

2.1.1 Agent Behavior

The model involves two groups of agents, passengers and vehicles. Each individual passenger generates a trip request from some origin location to some destination at some time. These trip demands are obtained from NYC yellow taxi records in June 2016. Besides trip generation, personal attributes such as their value of time (VoT) and maximum waiting time (patience) would affect their mode choice and order cancellation behaviors.

It is assumed that a passenger chooses a vehicle type (HV or AV) before the trip request. Such process is modeled as a Logit choice such that the utility depends on **(1)** the current trip fare, **(2)** individual VoT, and **(3)** the estimated waiting time to be matched with a vacant vehicle. In the case of undesirable utilities, passengers also have the option to select other modes, which have a fixed utility. Even if a passenger has requested for an AV or HV, the actual matching process might take too long so that they decide to cancel the request. A passenger is assumed to have some patience time (e.g., 1 minute, bounded by 0.5 and 2 minutes).

Both AVs and HVs provide the same trip services. They remain stationary until the platform (central system) assigns them with some passengers. They would pick up the passenger at the origin location by the shortest travel time path and deliver them to the destination in the same manner. The main difference is how the AV fleet can be directly managed by real-time activation/deactivation while human drivers are only partially influenced by monetary incentives. Since drivers have different inherent preferences about working hours and incomes, their participation and exit from the labor market are more complicated. It is challenging to predict their individual impacts on the aggregated market condition. Both income-targeting and neoclassical driver behaviors are considered in this paper. HVs drivers make relevant decisions based on either cumulative gain or the short-term income prospect.

2.1.2 Network and Matching

The road network of Manhattan is obtained from OpenStreetMap to build a directed graph with roads as edges and intersections as nodes. The resultant graph contains 9537 edges and 4360 nodes. Each edge is associated with a static travel time (i.e. constant speed), which is calibrated from historical taxi trip records. The static map is used to facilitate path-finding and trip assignment. A batch matching algorithm is used to pair waiting passengers and vacant vehicles. It operates at short intervals (e.g., 10 seconds) to pair the passenger requests queued during this interval with available vehicles such that the total pick-up travel time is minimized. Matching is conducted separately for AVs and HVs, as passengers cannot request both simultaneously.

2.2 Model Predictive Control

A model predictive control (MPC) scheme is applied in a closed-loop framework to maximize the platform's profit. The MPC relies on a prediction model to estimate future system states within a finite prediction horizon so that the control variables can be optimized with respect to future states. The optimization process is repeated with a shifted (receding) horizon to update the control inputs to be implemented in the simulation plant. In addition, the system model considers periodic state feedback from the plant to improve the state prediction. The overall system framework is illustrated in Figure 1. The set of 4 control inputs at a certain step k within the horizon, $\mathbf{u}(k)$, are **(1)** trip fare per unit in-vehicle travel time for AVs, $f^{AV}(k)$; **(2)** trip fare per unit in-vehicle travel time for HVs, $f^{HV}(k)$; **(3)** wage per unit in-vehicle travel time for HVs, $g^{HV}(k)$; and **(4)** AV fleet activation/deactivation, $N^{AV}(k)$.

By manipulating these control inputs, the platform aims to maximize its total profit for each receding horizon from k_0 to $k_0 + h$. The profit depends on (a) total revenues collected from AV and HV fares for each successful ride; (b) wage payments to HVs (i.e. HV cost); (c) fixed operational expenses of vacant and occupied AVs (i.e. AV cost); and (d) penalties from passenger order cancellations which affect long-term reputation of the platform.

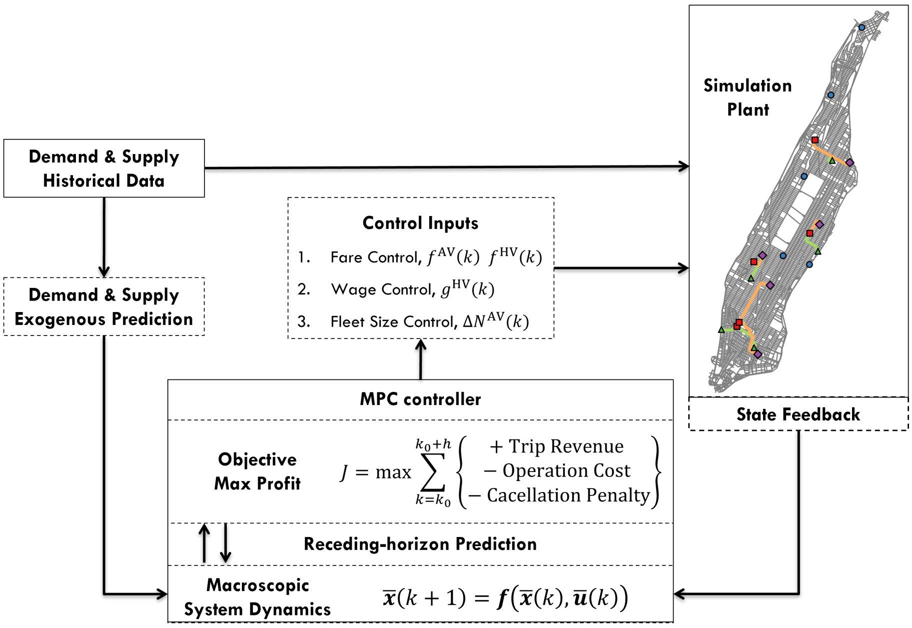

Figure 1 – *method framework. Historical supply and demand data are used as exogenous demand and supply estimations in the prediction model. The closed-loop framework involves state feedback from the plant, prediction of future states, optimization and implementation of control inputs.*

Equations 1–4 outline market state dynamics for the two vehicle types $m \in \{\mathsf{AV}; \mathsf{HV}\}$. The first two define the number of waiting passengers p_{w}^m, and vacant vehicles n_{v}^m of vehicle type m from time step k to $k+1$. The estimation requires exogenous demand N_{p}^m (including mode choice) and supply N^m inputs, as well as endogenous algorithmic estimations for the number of order cancellations $\hat{n}_{\mathsf{cancel}}^m$, number of expected drop-offs (trip completion) $\hat{n}_{\mathsf{drop}}^m$, and the number of new trip matching which is equal to the minimum of the two agent sets (p_{w}^m and n_{v}^m) in a complete bipartite graph. Likewise, the number of assigned vehicles n_{a}^m would decrease by the number of pick-ups $\hat{n}_{\mathsf{pick}}^m$, once they reach the passenger location and become occupied.

$$p_{\mathsf{w}}^m(k+1) = p_{\mathsf{w}}^m(k) + N_{\mathsf{p}}^m(k) - \hat{n}_{\mathsf{cancel}}^m(k) - \min\{p_{\mathsf{w}}^m(k);\ n_{\mathsf{v}}^m(k)\} \tag{1}$$
$$n_{\mathsf{v}}^m(k+1) = n_{\mathsf{v}}^m(k) + N^m(k) + \hat{n}_{\mathsf{drop}}^m(k) - \min\{p_{\mathsf{w}}^m(k);\ n_{\mathsf{v}}^m(k)\} \tag{2}$$
$$n_{\mathsf{a}}^m(k+1) = n_{\mathsf{a}}^m(k) - \hat{n}_{\mathsf{pick}}^m(k) + \min\{p_{\mathsf{w}}^m(k);\ n_{\mathsf{v}}^m(k)\} \tag{3}$$
$$n_{\mathsf{o}}^m(k+1) = n_{\mathsf{o}}^m(k) + \hat{n}_{\mathsf{pick}}^m(k) - \hat{n}_{\mathsf{drop}}^m(k) \tag{4}$$

The controllers manage the system via the exogenous demand and supply. Trip fares would determine the passenger demand and the mode split ratio; AV fleet size is a direct control variable; and dynamic driver wages are indirect incentives to manage the HV supply.

3 RESULTS

The preliminary results suggest that MPC has the potential to significantly improve the profit. The test case simulates the morning passenger demand based on historical taxi trip records from 04:00 to 10:00 with 1000 AVs and HVs respectively. The benchmark control variables are assumed to be time-invariant. Figure 2 shows an example of state prediction for the benchmark case. Plant feedback adjusts the initial guesses for each prediction. Table 1 summarizes results for a scenario where only passenger fares are controlled. Thus, the solution for a supply surplus is to increase both fares to gain more profits, which also drive out passengers, those above the platform's capacity, to lower the expected order cancellation. The AV fare is raised to an average of $\$1{:}52$/min (from $\$0{:}8$/min) and HV fare is raised to $\$1{:}67$/min (from $\$0{:}7$/min).