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Simulation and management of mixed autonomous and human-driven ride-sourcing fleets

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1.Introduction

With the advance of self-driving technologies, ride-hailing companies would likely deploy their company-owned fleets of automated taxis (a-taxis) to explore new business opportunities and benefits. Therefore, this research aims to investigate the effects of a mixed fleet of vehicles, autonomous and human-driven, in the market. It tries to optimise relevant operational variables to maximise the platform's profit and improve the overall service quality.
Since the sharing economy and autonomous vehicle (AV) concepts are relatively new, there exits only a few publications investigating the operation of a mixed fleet and market segmentation. Most fleet management and dispatching studies focus on a single mode, either traditional taxis or ride-hailing vehicles (Horn, 2002; Maciejewski et al., 2016; Nourinejad and Ramezani, 2020). This paper identifies optimal price and wage structures for human-driven vehicles (HVs) while controlling the fleet size of active AVs. By utilising an event-based simulation as the plant, this research applies a model predictive control (MPC) approach based on a market state model.

2. Market simulation

The overall simulation structure can be summarised with four components, a group of individuals (passengers) interact with another group (vehicles including AVs and HVs) via a mechanism (trip match algorithm) in an environment (road network).

The simulation considers the road network in Manhattan. Geographic information is obtained from OpenStreetMap before they are filtered (to remove irrelevant road types), pruned (to remove unconnected roads or isolated sub-network), and grouped (to reduce duplicated or very close coordinates). The result is a strongly connected directed graph, with roads as edges and intersections as nodes. In this simulation, microscopic traffic conditions are simplified by assigning time-invariant unique road speeds which are pre-calculated and calibrated.

Passengers are constructed based on New York City Taxi & Limousine Commission (NYC TLC) yellow taxi trip records in June 2016. Passengers make trip requests based on historical data. In addition, a passenger needs to select a type of vehicle between AV and HV before requesting, and the passenger may cancel the request if it takes too long to be assigned to a vehicle of the chosen type.
Three types of service vehicles are available: an autonomous vehicle (AV), a human-driven vehicle (HV), or any other mode of transportation such as active modes or public transport (others). This decision-making is simulated by a Logit choice model based on the generalised cost (GC) of each choice as its (dis)utility which consists of a monetary cost (trip fare) and a non-monetary cost (waiting time), as shown in the following equation:

$$\mathrm{GC}^m = (f_1^m(t) + f_2^m(t)\, t_\mathrm{o}) + \omega\, (\phi^m\, t_\mathrm{a}^m) \qquad \forall\, m \in \{\mathrm{AV}, \mathrm{HV}\}$$

where,

GC^m is the generalised cost of vehicle type m, which is either an AV or HV;
$f_1^m(t)$ is the flag-off fee, which is a time-varying control variable;
$f_2^m(t)$ is the add-on price per unit time, which is a time-varying control variable;
t_o is the expected trip time for the passenger;
ω is the passenger value of time, used to quantify the non-monetary cost;
t_a^m is the waiting time to the nearest vacant vehicle of type m when making a request;
ϕ^m is an approximation coefficient to calculate the estimated waiting time from t_w^m.

Without loss of generality, GC for other modes is grouped and assumed to be fixed as $25. Once a passenger selects either an AV or HV, the platform would try to assign a vacant vehicle to the trip request based on the matching algorithm (see Section 2.4). If the passenger selects other modes or fails to be assigned a vehicle for some extended time, the request would be cancelled which incurs penalties. In this simulation, a passenger may wait for some time ranging from 30 to 90 seconds.

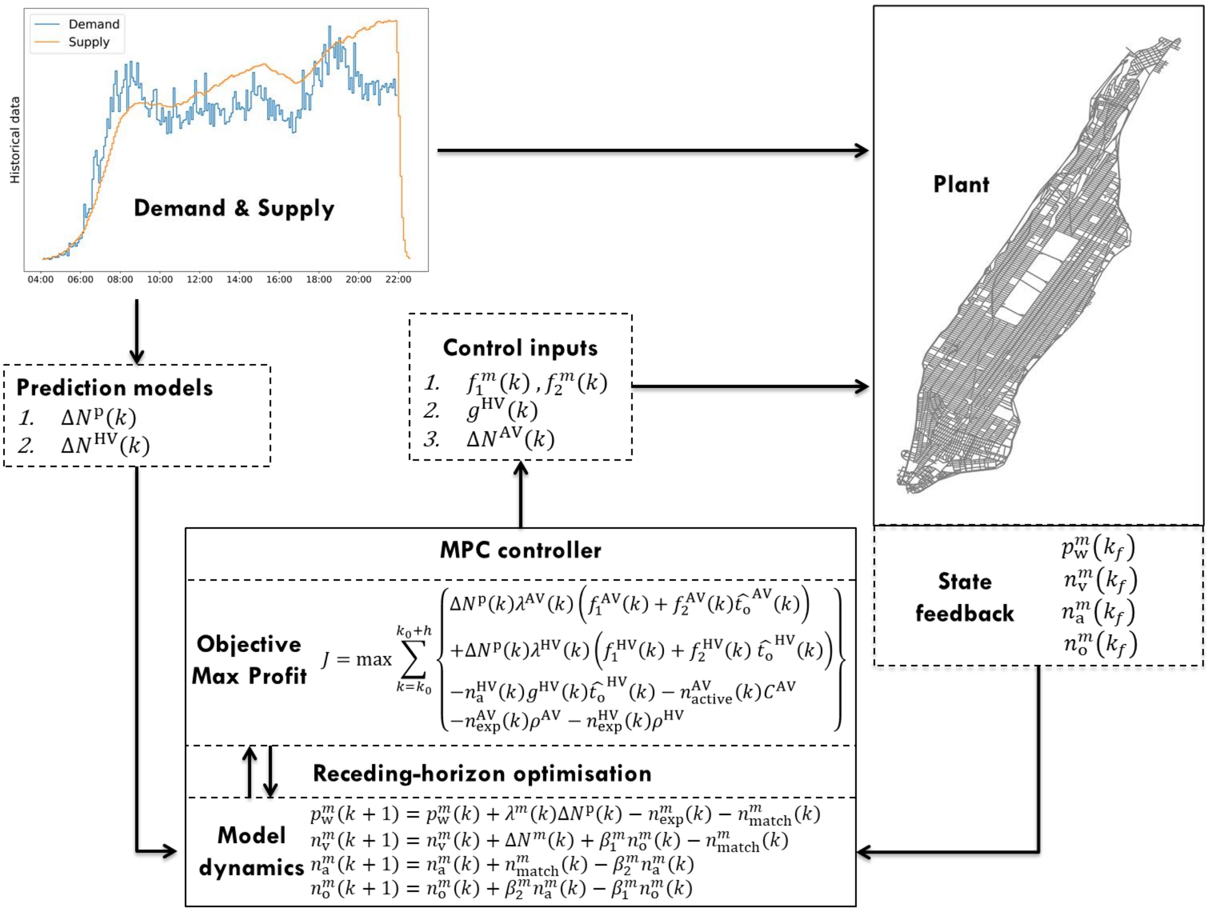
This paper considers two main labour market theories: the neoclassical theory and the income-targeting theory. Generally, neoclassical drivers are motivated to work more when the wage is higher because of the higher expected income (Farber, 2015). In contrast, income-targeting drivers have a desired level of daily income, so they would stop working after reaching it. A higher wage could cause earlier termination and fewer work hours (Camerer et al., 1997).
Each neoclassical HV has an opportunity cost to compare against the expected gain of working in the ride-sourcing market. This cost represents alternative preoccupations so that it is only profitable to work if the benefit exceeds the cost. The expected benefit is calculated as the product of the system utilisation ratio θ^{HV}, and the dynamic wage g^{HV}. The value of θ^{HV} is calculated as the ratio of occupied HVs to total HVs, updated after each drop-off. Likewise, drivers make the same comparison to decide whether to leave or stay in the market. Each income-targeting HV has a daily income goal. Different targets can reflect whether the driver prefers full-time or part-time shifts. An income-targeting HV would always start working at their preferred starting times, and end working after a passenger drop-off if the target is reached.

Without repositioning, a vacant vehicle remains stationary until the matching system assigns it to a waiting passenger. The assigned vehicle picks up the passenger and moves to the requested destination via the shortest travel time path, then waits for the next assignment. AV supplies are directly managed (by the company), while HV supplies are more unpredictable and dynamic as a result of individual driver's work preferences.
The demand and supply are matched via a central platform. A batch matching algorithm with a fixed interval (e.g. 10 seconds) is used to pair a set of unassigned trips with vacant unassigned vehicles. A complete bipartite graph is used to represent all possible pairs with each edge weight representing the travel times for pick-ups. A minimum-weight full matching solution thus gives the optimal assignment plan. For a complete bipartite graph, the number of matched pairs is equal to the size of the limiting set, thus there are $\min\{p_\mathrm{w}(t), n_\mathrm{v}(t)\}$ assignments at time t, with p_w waiting passengers and n_v vacant vehicles. Matching is conducted separately and independently for AVs and HVs at every interval.

3. Market control

Market management can be dynamically optimised with a model predictive control (MPC) approach. The MPC uses a state prediction model to estimate future market conditions within a definite horizon and optimise variables such as wages offered to HVs, passenger fares, and the fleet size of AVs to maximise platform's profit. Figure 1 illustrates the method framework with two main parts, the simulation plant and the MPC. The plant models individual behaviours and market dynamics (Section 2). The MPC is executed at discrete time intervals to maximise the net profit which consists of revenues from passenger fares, expenditure from HV driver wages, and AV operational expenses. Order cancellations induce penalties in the objective as the service quality is compromised.

Figure 1: Methodology framework. The plant simulates market interactions between passengers, drivers, and AVs. The controller relies on a dynamic state prediction model to optimise control inputs and maximise platform profit. The model receives state corrections from the plant at specific instances. The MPC computes the optimal control values in a receding horizon manner.



The market states are modelled as a set of difference equations. Vehicle states change from (v)acant, to (a)ssigned, then (o)ccupied, and finally vacant again via the matching, picking-up, and dropping-off events respectively. Variable $\Delta N^m(t)$ is the net number of vehicles entering/exiting the market, which is controlled for AVs and estimated for HVs; $\Delta N^{\mathrm{p}}(t)$ is the number of new passenger requests; $\beta_1,\ \beta_2,\ \beta_3$ are a linear coefficients for estimating passenger drop-offs, pick-ups from assignments, and order cancellations respectively.

MPC-optimized variables include passenger fare prices $\{f_1^{\mathrm{AV}}(k),\ f_2^{\mathrm{AV}}(k),\ f_1^{\mathrm{HV}}(k),\ f_2^{\mathrm{HV}}(k)\}$, wages offered $g^{\mathrm{HV}}(k)$, and the change in AV fleet size $\Delta N^{\mathrm{AV}}(k)$. 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 (i) revenues from passengers choosing either HV or AV service, reserved when making trip requests; (ii) wage payments to HVs, registered when assigned to passengers; (iii) constant operational cost of active AVs; and (iv) penalties from passenger order cancellations which offset the respective reserved revenues.

4. Results

Table 1 presents simulation statistics for two scenarios to demonstrate how the plant reacts to changes in driver wage rates. The first scenario applies a constant wage rate throughout the simulated period and the second scenario applies time-varying rates. Wages are manually increased to attract more drivers to participate during peak hours, such that passenger demand can be better served. As the result indicates, a higher unit wage can attract more neoclassical drivers and reduces the total number of order cancellation. However, it also leads to more expenditure paid to drivers and eventually less overall profit. Although this specific pricing plan is not optimal, it shows how the wage variable can impact the market operation.

Table 1: Simulation statistics

	Scenario 1	**Scenario 2**
Passenger fare (fixed)	HV = \$3 + \$0.8/min in-vehicle travel time AV = \$6 + \$0.6/min in-vehicle travel time	
AV fleet size (fixed)	200	
HV wage rate	\$50/hr (fixed)	\$50/hr (04:00 – 07:00) \$60/hr (07:00 – 11:00) \$40/hr (11:00 – 18:00) \$60/hr (18:00 – 22:00)
Passenger mode choice HV/AV/others	39801 / 9932 / 16052	39331 / 10074 / 16380
Total assignments HV/AV	33748 / 8940	34215 / 8879
Total order cancellation HV/AV	6053 / 992	5116 / 1195
Total profit	\$147,841.34	\$86,076.15
Trip statistics (HV / AV)		
Median trip distance (m)	6145 / 7319	6122 / 7195
Median trip time $\bar{t_o}$ (min)	9.77 / 11.65	9.75 / 11.55
Median pick-up time $\bar{t_a}$ (min)	6.00 / 8.12	6.45 / 8.20
Median trip fare (\$)	\$10.81 / \$12.99	\$10.80 / \$12.93
HVs (neoclassical / income-targeting)		
Total participation	557 / 1283	903 / 1242
Median daily income	\$69.10 / \$117.32	\$103.01 / \$136.48
Median hourly income	\$22.50 / \$22.90	\$28.48 / \$28.73
Median work hours	3.06 / 5.18	3.28 / 4.60

Figure 2: 30-minute rolling horizon prediction of market states between 08:00 and 09:00, with historically fitted $\boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \boldsymbol{\beta_3}$ parameter values. The plant corrects state values every 5 minutes. Exogeneous demand and supply values are assumed to be given. Grey lines are the actual values and coloured lines are predictions.

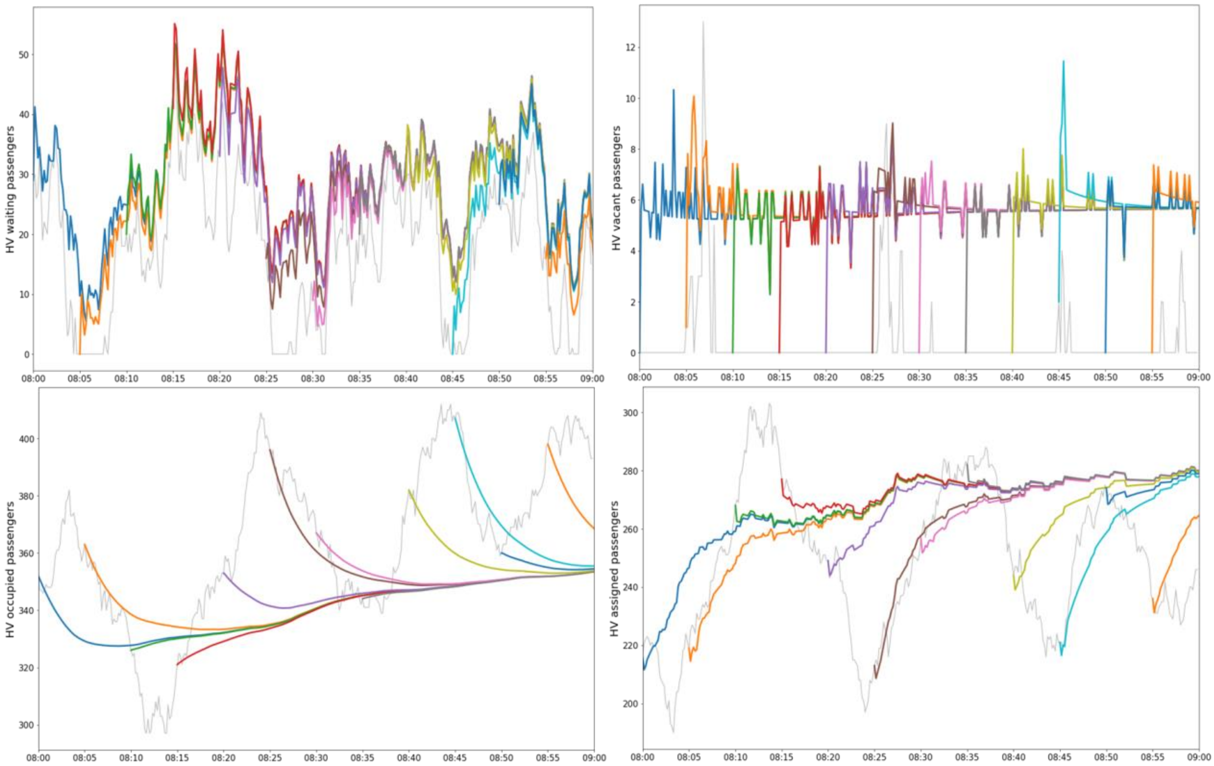


Figure 2 plots the predicted system state values based on dynamics described in Figure 1. Parameter values $\beta_1^m,\ \beta_2^m,\ \beta_3^m$ are obtained from linear regression models of historical system data for both AVs and HVs. The simulation set state corrections every 5 minutes such that values can be estimated for the next 30 minutes. Exogeneous demand and supply values are assumed to be known in this example to show how well the linear coefficients can predict market conditions. As shown in the figure, the fluctuation in p_{w}^m can be captured if the number of new demands is known. However, the fluctuation in n_{a}^m and n_{o}^m is not always reflected by assuming linear coefficients. This suggests a more complicated model may be necessary.

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