Repositioning ridesplitting vehicles through pricing: A two-region simulated study

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1 INTRODUCTION

Every day ride-sourcing services grow and promote new service options at the same time that regulators try to identify and mitigate the negative externalities of these operations to the society (Rayle *et al.*, 2016).

Geographical variations on demand can create an unbalance between service demand and driver supply. In this direction, keeping drivers well positioned is of vital importance to maintain a satisfactory service quality. Most strategies in the literature are reactive in the sense that they rely on past events such as losses of requests. However, if customers face recurrent losses, they are likely to change to a mode that is always ready to serve them.

MFD-based models can describe the dynamics of state evolution in urban networks partitioned in a number of homogeneously congested regions to predict near future conditions. Examples of its use include taxis and ride-hailing (solo rides) (Nourinejad & Ramezani, 2020). Note that, the studies still lack the effects of ridesplitting on repositioning strategies and detailed analysis on driver decision process. The reader is acknowledged that this does not configure a systematic, nor comprehensive literature review, which will come in the final version of the paper.

Herein, we develop relocation strategies for ride-sourcing vehicles using a fare optimization controller subject to a dynamic MFD-based model as Beojone & Geroliminis (2021), which also provides drivers with an estimate for their earnings according to their repositioning decisions. The fleet operator uses a continuous-time Markov chain to estimate earnings for a given decision. To the best of our knowledge, this is the first attempt to integrate fare optimization and repositioning in a scenario with ridesplitting.

2 MODEL DESCRIPTION

The model assumes that the TNC provides two service options that idle drivers can serve. The first option, ride-hailing, aims customers that prefer to pay higher fares to ride alone. The second one, ridesplitting, aims customers that accept some detour and longer travel times in exchange for cheaper fares. Another important assumption is that ridesplitting is limited to serve two passengers simultaneously per vehicle, which can comply with most of the current data on ridesplitting. Table 1 is derived from the list of activities. Pick-up and drop-off activities were aggregated to form a single state. Vehicles in states RH and $S2$ are assumed completely busy and cannot receive new assignments. At the same time, vehicles in states I and $S1$ are considered available for new assignments ($S1$ only for ridesplitting assignments). For simplicity, we assume that private vehicles actions besides driving (e.g. cruising for parking) are negligible.

Table 1 – *List of states based on the activities vehicles perform.*

Activity	State	Accumulation	Activity	State	Accumulation
Idle	I	$n_o^I(t)$	Single ridesplitting	$S1$	$n_{od}^{S1}(t)$
Repositioning	RP	$n_{od}^{RP}(t)$	Shared ridesplitting	$S2$	$n_{od}^{S2}(t)$
Ride-hailing	RH	$n_{od}^{RH}(t)$	Private vehicle	PV	$n_{od}^{PV}(t)$

To summarize the description states and activities of ride-sourcing and private vehicles, Figure 1A presents the state space with their respective transitions. The urban area is composed of a set $\mathcal{R} = \{1, 2\}$ of regions. Mass conservation equations [1] keep track of the number of vehicles in each state and their remaining distance to be traveled in an M-Model (Sirmatel *et al.*, 2021). The only exception is for idle ride-sourcing vehicles, which have no trips to complete. Instead, they cruise waiting for the assignment of a new passenger (similarly to cruising for parking), thus, there is no remaining distance, only the number of vehicles.

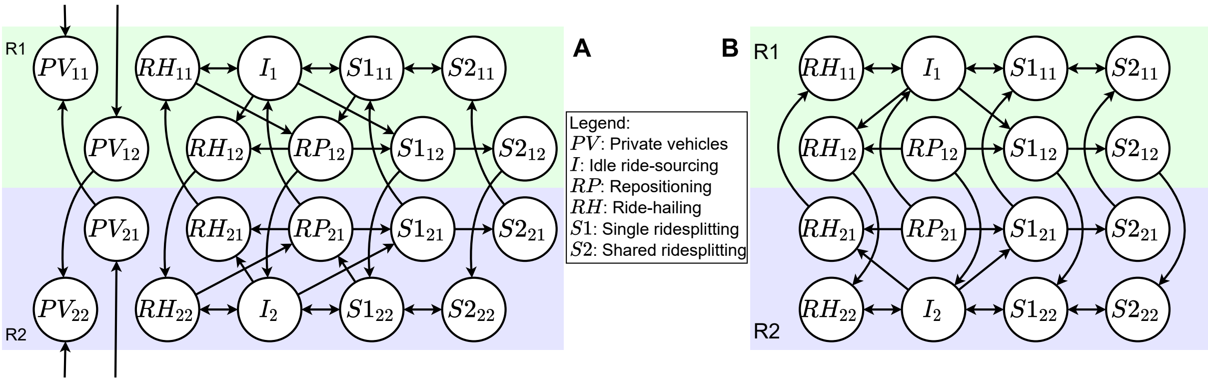

Figure 1 – *(A) Two-region state-space for ride-sourcing vehicles and private vehicles with their schematic state transitions in the MFD-based model (system level model). (B) Ride-sourcing driver state-space and transitions in the Markov chain model (individual level model).*

$$\dot{n}_{od}^K(t) = I_{od}^K(t) - O_{od}^K(t) \tag{1a}$$
$$\dot{M}_{od}^K(t) = I_{od}^K(t) L_{od}^K(t) - n_{od}^K(t) v_o(t) \tag{1b}$$

Where $n_{od}^K(t)$ and $M_{od}^K(t)$ are the number of drivers and the total remaining distance to be travelled for drivers at an activity K at area o to area d, respectively. Furthermore, $I_{od}^K(t)$ and $O_{od}^K(t)$ represent the total inflows and outflows for these drivers, respectively. $L_{od}^K(t)$, in the other hand, is their average trip length and $v_o(t)$ is the current average speed at that area.

Given the large frequency of events (passenger arrivals, deliveries, transfer flows) one can approximate the revenue generation for the company by means of a continuous rate (instead of a service by service basis). Furthermore, if the regions are reasonable uniform, we can assume that drivers split earnings equally. Therefore, drivers' earning generation depends on the activity they are performing and booking and distance fares.

We assume that drivers try to maximize their earnings but they are unable to accurately estimate earnings themselves (due to limited information and rationality). To help drivers, the service provider uses a continuous-time Markov chain to depict near-future activities and earnings of individual drivers. Figure 1B depicts the transitions on the Markov chain. Note that this Markov chain is depicted on an individual level, i.e., arrival rates, trip-completion and transfer flows are individualized based on current information of the MFD model. Moreover, it assumes that drivers will only make this decision the moment they are about to become idle, therefore, there is no transition from idle to repositioning state because the probability making this decision again in the near-future is negligible.

$$\dot{\pi}_{od}^{K}(t) = -\tilde{O}_{od}^{K}(t)\pi_{od}^{K}(t) + \sum_{k} \tilde{I}_{od}^{k}(t)\pi_{od}^{k}(t) \tag{2}$$

Where $\pi_{od}^{K}(t)$ is the instantaneous probability of a driver being in state K_{od}; and $\tilde{O}_{od}^{K}$ and $\sum_k \tilde{I}_{od}^{k}\pi_{od}^{k}(t)$ are the individualized outflows and sum of inflows towards state K_{od}. The starting solutions of the Markov chain represent drivers' possible decisions, and their resulting probabilities are used to estimate their earnings. Earnings from derive from bookings and traveling, which are computed from to the number of new assignments and the production of busy drivers, respectively. A logit model depicts drivers' final decisions back into the MFD-model.

3 MODEL PREDICTIVE CONTROLLER

In this prototype application, we consider that the objective is to decrease the number of lost ride requests for ride-sourcing services (called abandonments). Moreover, the responsible for setting fares and supplying drivers with estimates on their near-future earnings is the service provider, which can control booking and traveling fares independently within a bounded range ($[f_{B,\min}^{s}, f_{B,\max}^{s}]$ and $[f_{T,\min}^{s}, f_{T,\max}^{s}]$). The design of the fare optimization problem of the ride-sourcing service is formulated in Equation [3].

$$\min_{f_B^s(t), f_T^s(t)} \quad J = \int_{t_0}^{t_f} \sum_{s \in \mathcal{S}} \sum_{(o,d) \in \mathcal{R}^2} pl_{od}^{s}\left(v_o(t), n_{av}^{s}(t)\right) \lambda_{od}^{s}(t)\, dt \qquad n_{av}^{s}(t) = \sum_{k_s \in \mathcal{K}_s} n_{od}^{k_s}(t) \tag{3a}$$

$$\text{s.t.:} \quad \text{Equation [1]} \qquad t \in [t_0, t_f] \tag{3b}$$

$$f_{B,\min}^{s} \leq f_{B}^{s}(t) \leq f_{B,\max}^{s} \qquad t \in [t_0, t_f] \text{ and } s \in \mathcal{S} \tag{3c}$$

$$f_{T,\min}^{s} \leq f_{T}^{s}(t) \leq f_{T,\max}^{s} \qquad t \in [t_0, t_f] \text{ and } s \in \mathcal{S} \tag{3d}$$

$$v(t), n_{od}^{K}(t), ... \geq 0 \qquad t \in [t_0, t_f] \tag{3e}$$

In the objective function (Equation [3a]) the total number of lost passengers is described using $pl_{od}^{s}(t)$ (probability of losing an arriving passenger), and $\lambda_{od}^{s}(t)$ (passenger arrival rate for a service $s \in \mathcal{S} = \{H, S\}$ – trisride-hailing or ridesplitting). Equation [3b] summarizes the mass conservation equations of the MFD-model in Equation [1]. Equations [3c] and [3d] bound the values for fares. Finally, Equation [3e] guarantees that the states of the model remain non-negative. In this prototype implementation, we neglect the market effects on customers and drivers decisions for joining or leaving the system. This is a direction for further research.

We prepared a rolling time horizon MPC controller. At each time step of 3 minutes, the controller tries to minimize abandonments for the next 10 time-steps. The feedback loop provides an estimation of system states. The optimization output is the set of fares. Fares affect indirectly loss probabilities and outflows, therefore we solve the problem with a pattern search algorithm at each step. We assume that the demand prediction module is based on historical data.

4 COMPUTATION RESULTS

The observation of abandonment rates shows how repositioning has potential to decrease the number of lost requests. Fixing fares and allowing drivers to move between regions according to their expectations on revenues was capable to decrease the number of lost requests by more than 70%. Optimizing fares dynamically, brought abandonments to a near-zero situation, decreasing by 98% compared to the non-repositioning scenario. However, the impacts of these decisions on traffic are secondary to the problem as shown in Figure 2, where the optimization of fares decreased the travelling speeds, in general. Furthermore, the greatest decreases in speed were in the most congested periods of each region. We must point out that, in all cases, travelling speeds remained above the critical speeds (13 km/h), i.e., the system never entered a hyper-congested state (accounting for the background traffic as in Figure 1A).

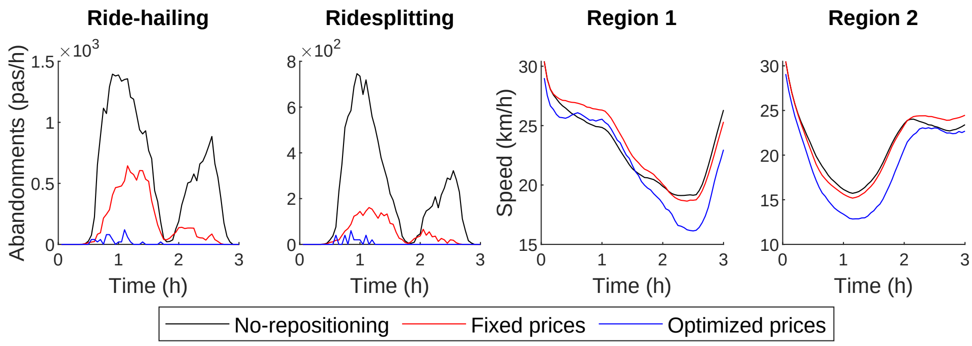

Figure 2 – *Comparison of realized abandonments and average travelling speed among three scenarios for (left) ride-hailing and (right) ridesplitting). Measurements extracted from the simulation/plant results for each time-step of 3 minutes.*

5 FINAL CONSIDERATIONS

In this paper we developed relocation strategies for ride-sourcing vehicles using a fare optimization controller which also provides drivers with an estimate for their earnings for their repositioning decisions. Our main results show that repositioning could brought passenger abandonments to a near-zero scenario at the expense of decreasing travelling speeds, especially at the moments of higher demand.

Such findings are expected in a problem with a single objective (minimize abandonments). We must highlight that, in this case, the decrease in abandonments is a lot more pronounced than the decrease in speeds, which did not enter a hyper-congested state. More evidence is needed but these findings provide a likely path for testing the impacts of different regulatory strategies under a transient situation. Nevertheless, this work contributes by expanding the test of fare optimization to ride-sourcing services with the presence of ridesplitting option and providing a powerful tool to estimate near-future earnings through a Markov chain, given the additional options drivers and passengers have in these travel modes.

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