An auctioning process for large-scale ride-hailing vehicles repositioning

M. Seppecher*[1], L. Leclercq[1]

[1] Univ. Gustave Eiffel, Univ. Lyon, ENTPE, LICIT-ECO7 UMR T9401, F-69675, Lyon (France)

SHORT SUMMARY

On-demand mobility services are transforming urban mobility. They can provide individual and collective benefits when managed optimally, and their successful integration within the existing urban transport system can enhance its performance. In contrast, inadequate fleet management can inflict high pick-up waiting times and passenger drop-out rates. One of the main challenges for on-demand mobility service operators is to proactively rebalance their fleets to ensure that the spatial distribution of supply matches the demand. This paper proposes to address this problem with a distributed auctioning approach. We design an architecture that relies on local controllers interacting with idle vehicles, encouraging them to relocate to their service area. We conduct simulations on the city of Lyon in France, which reveal a substantial increase in the number of passengers served compared to a scenario without rebalancing.

Keywords: auctioning, fleet management, multi-agent modeling, on-demand services, ride-hailing, simulation.

1. INTRODUCTION

Over the last decades, novel mobility services have appeared in cities, such as ride-sourcing (including e-hailing and ride-splitting) and vehicle sharing. In particular, ride-sourcing companies have multiplied, competing with traditional taxi companies and providing travelers with a vast range of services. This new offer can meet an increasingly dynamic and non-regular mobility demand, unsatisfied by public transportation or personal car constraints. On one side, ride-sourcing services offer more flexible services than public transit, on-spot and on-demand pick-up, and no connections. On the other side, they can be less costly than private car ownership and provide satisfying solutions to parking issues. At a collective scale, the services can contribute to limiting car ownership and its externalities, such as land occupancy, soil sealing, or congestion.

However, efficiently managing this type of service requires handling several operational issues. Fleet rebalancing is one of them. It consists of reorganizing a vehicle fleet in space and time by dispatching idle vehicles towards high-demand areas to limit vehicle accumulation in attractive zones and ensure continuous and prompt service to passengers.

Rebalancing must preferably be proactive, *i.e.*, anticipate the future demand and reorganize the fleet accordingly. Numerous literature studies have looked at this management issue. Yet, most offer centralized management methods, raising questions regarding their robustness to scaling or communication failures (Alonso-Mora et al., 2017; Miao et al., 2017, 2015; Ramezani and Nourinejad, 2018). In this respect, distributed approaches are interesting alternatives. Recent works have looked into fleet rebalancing through the lens of passengers and drivers-intended incentives, with pricing and information-sharing strategies or coverage control (Zhu et al., 2022). In this work, we explore this subject through the angle of auctioning. While auctioning approaches have been applied for developing (reactive) matching strategies (Manjunath et al., 2021; Nourinejad and Roorda, 2016; Wu et al., 2008), this is, to our knowledge the first attempt to extend its application to fleet large scale repositioning.

2. METHODOLOGY

The method we develop relies on a mesh of controllers that divide the urban network into an equal number of service areas. These controllers, which can be associated with physical infrastructures such as taxi stations and deposits, are considered at the service of a public authority (*e.g.,* local authority or transport agency). Their goal is to ensure that ride requests occurring within the boundaries of their service area are served with the minimum waiting time. For this purpose, they aim to attract idle vehicles within their perimeter by negotiating with them at regular intervals (*e.g.*, every 10 minutes) within a **two-sided matching market**.

With this frequency, the controllers are first in charge of forecasting the future demand (*i.e.*, the number of requests). The specific topic of demand forecasting is out of the scope of this paper, and we will assume that historical data allow modeling the future number of requests as a random variable $X = N(\mu_i^T, (\sigma_i^T)^2)$. This assumption is supported by recent research in demand prediction (Khalesian et al., 2022). To attract the required number of vehicles, local controllers publish within the matching market as many **relocating offers** as expected ride requests. These offers will allow vehicles to which they are assigned to relocate within the corresponding service area. Each relocation offer is characterized by:

1. The likelihood of the expected ride request. We define the likelihood p_k of the k$^{\text{th}}$ expected ride request as the probability that at least k ride request occur during t. Therefore, we have:
$$\forall k \in \mathbb{N},\ p_k = S_X(k) = P(X \geq k) \quad (1)$$
with S_X the survival function of X.
2. The expected revenue $\hat{g}_i$ for picking up a passenger in service area i, which can be estimated based on historical data.

Then, the matching of vehicles with a relocation offer follows a **distributed Gale-Shapley algorithm** (Brito and Meseguer, 2006, 2005), often used to solve matching problems (marriage, student-college or resident-hospital matching). First, the features of relocating offers allow drivers to estimate their utility in applying to one or another relocation option. This utility is estimated as the expected net revenue, computed as the difference between expected incomes (expected revenue weighted by request likelihood) and rebalancing costs:

$$U_v(i,k) = p_k\, \hat{g}_i - c_v(i) \qquad (2)$$

Drivers bid on the most useful relocating option and share their expected arrival time within the region with the local controller. Then, local controllers rank the received offer according to their utility. For each relocation offer, the controller accepts its preferred application and rejects the others. Rejected vehicles update their preference list and apply to their second most-preferred option. If a controller previously now receives a better application, it can reject the previously-matched vehicle and accept the new one. The rejected vehicle updates its preference list and applies to another relocation offer. This process goes on until all cars run out of interesting relocation offers. In the end, vehicles matched relocate to their destination region, and unassigned vehicles remain idle at their current position. Although iterative, this process can be close to instantaneous, as drivers actually do not interfere in the process. We illustrate this communication protocol in Figure 1.

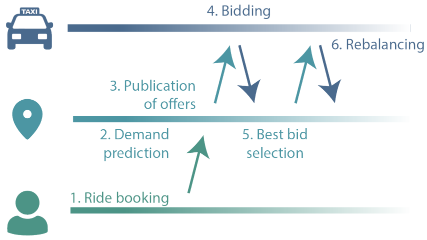

Figure 1: Communication protocol supporting the fleet rebalancing

Note that controllers can use several methods to evaluate the utility of the application of a vehicle. In the present paper, we use the following approach. A fictive occurrence time within the rebalancing period is assigned to each expected ride request. Then, the utility of a vehicle application is determined according to the delay the travel time the vehicle needs to join the service area would inflict on this expected passenger, given this fictive occurrence time. The utility function is triangular, maximal when the car arrives right on time, and decreases faster when the vehicle comes later than when it arrives in advance, as illustrated in Figure 2.

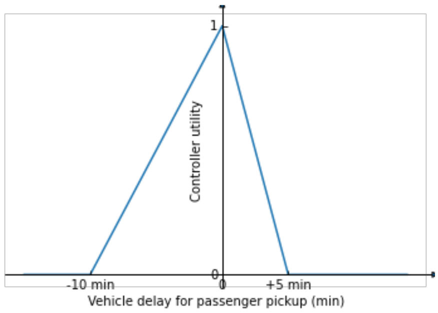

Figure 2: Controllers' utility

3. RESULTS AND DISCUSSION

Case study

We choose the city of Lyon, France, as a case study. The network we model covers 121 km2 and includes both the city of Lyon and the city of Villeurbanne, located within a circular ring road. To conduct rapid simulations, we model the traffic on a simplified network of the city. The network only includes the primary and secondary urban roads and highways, as illustrated by Figure 2.a). The supply calibration and the demand scenarios used here have been calculated within the ERC Magnum Project (Mariotte et al., 2020). 15% of the inner flows are assigned to ride-hailing, while the remaining users are assumed to take their personal cars. The city is partitioned into 50 service areas, as illustrated in Figure 2.b). The simulations are conducted on the MnMS multi-agent simulation platform developed at Univ. Gustave Eiffel. This paper presents the results of simulations performed with a 4000-vehicle-large vehicle fleet and 10-minute-long passenger waiting time tolerance.

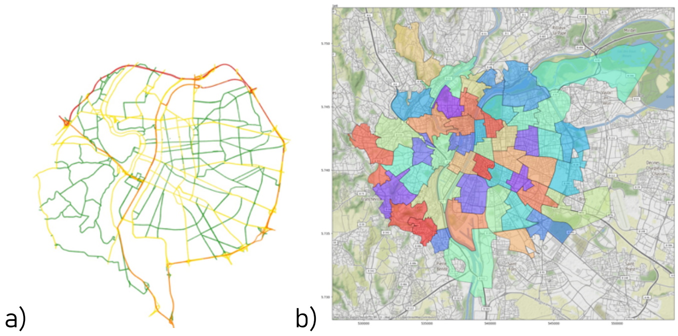

Figure 2. Simulation network. a) Road network. b) Service areas.

Results

We compare our strategy to a no-rebalancing scenario and evaluate performance based on several KPIs regarding service, users, drivers, and traffic. First, our analyses show that implementing our strategy over the city of Lyon allows increasing the number of passengers served by 9.88% (+1975 passengers) compared to the base scenario. This service increase is especially significant between 8:00 a.m. and 9:00 a.m., during the peak demand hour, as illustrated in Figure 3. Figure 4 shows the level of service improvement in space. Applying our rebalancing strategy especially allows for increasing the service in the western suburban and less connected areas of the city (+32% of demand served in some areas) while being slightly detrimental to the service in the city center and eastern neighborhoods. We observed that this overall service improvement comes with an increase in waiting time before pick-up of 1.39 minutes on average. This increase is explained by the decrease in the number of available vehicles, due, on the one hand, to the rise in the number of passengers served, on the other hand, to rebalancing vehicles being considered unavailable for matching. Exploring variants of this rebalancing strategy that allow rebalancing vehicles to pick up passengers should allow limiting this waiting time increase.

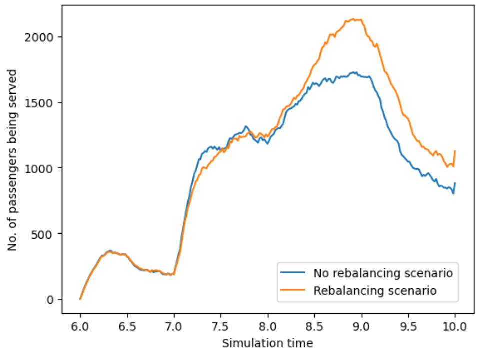

Figure 3: Number of users being served throughout simulation time.

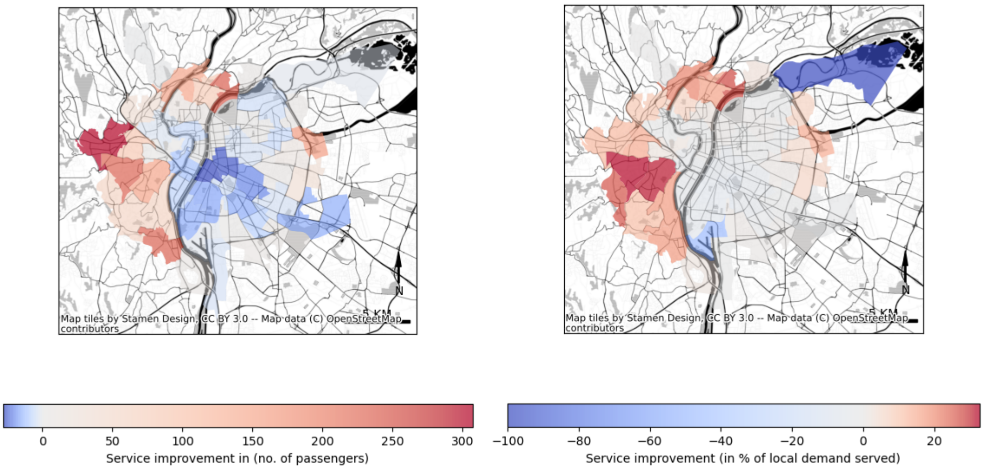

Figure 4: Spatial visualisation of the service improvement thanks to rebalancing.

4. CONCLUSIONS

In this paper, we propose an original fleet rebalancing strategy based on outsourcing rebalancing management to local controllers and implementing a negotiation process between them and the vehicles. Our method significantly impacts the number of passengers served, especially in suburban areas less connected to the city center. Although it also seems to increase the average waiting time of passengers, this increase is limited compared to the increase in the number of passengers served, and more flexible matching strategies will help to mitigate this effect.

As a continuation of this work, future works will focus on conducting advanced sensitivity analyses to fleet size, uncertainty levels, or riding fares. We will also explore different utility functions for local controllers and assess their impact on waiting time, amount of passengers served, or empty mileage.

In the mid-term, we will use this approach to develop local incentive strategies to encourage vehicles to relocate to service areas with lower accessibility or uncertain demand. We will also look at enriching the method to foster cooperation between local controllers rather than competition. Finally, this approach based on controllers external to the service could be relevant in managing the competition between different mobility services.

ACKNOWLEDGEMENTS

This project has received funding from the European Union's Horizon 2020 research and innovation program under Grant Agreement no. 953783 (DIT4TraM).

REFERENCES

Alonso-Mora, J., Wallar, A., Rus, D., 2017. Predictive routing for autonomous mobility-on-demand systems with ride-sharing, in: 2017 IEEE/RSJ International

Conference on Intelligent Robots and Systems (IROS). Presented at the 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 3583–3590. https://doi.org/10.1109/IROS.2017.8206203

Brito, I., Meseguer, P., 2006. Distributed Stable Matching Problems with Ties and Incomplete Lists, in: Benhamou, F. (Ed.), Principles and Practice of Constraint Programming - CP 2006, Lecture Notes in Computer Science. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 675–679. https://doi.org/10.1007/11889205_49

Brito, I., Meseguer, P., 2005. Distributed Stable Matching Problems. Presented at the LNCS, pp. 152–166. https://doi.org/10.1007/11564751_14

Khalesian, M., Furno, A., Leclercq, L., 2022. High-Resolution Traffic Demand Prediction, Based on Deep Learning and Hierarchical Reconciliation. Transportation Research Part C: Emerging Technologies. https://doi.org/10.2139/ssrn.4250272

Manjunath, A., Raychoudhury, V., Saha, S., Kar, S., Kamath, A., 2021. CARE-Share: A Cooperative and Adaptive Strategy for Distributed Taxi Ride Sharing. IEEE Transactions on Intelligent Transportation Systems 1–17. https://doi.org/10.1109/TITS.2021.3066439

Mariotte, G., Leclercq, L., Batista, S.F.A., Krug, J., Paipuri, M., 2020. Calibration and validation of multi-reservoir MFD models: A case study in Lyon. Transportation Research Part B: Methodological 136, 62–86. https://doi.org/10.1016/j.trb.2020.03.006

Miao, F., Han, S., Lin, S., Stankovic, J.A., Huang, H., Zhang, D., Munir, S., He, T., Pappas, G.J., 2015. Taxi Dispatch with Real-Time Sensing Data in Metropolitan Areas: A Receding Horizon Control Approach. Proceedings of the ACM/IEEE Sixth International Conference on Cyber-Physical Systems 100–109. https://doi.org/10.1145/2735960.2735961

Miao, F., Han, S., Lin, S., Wang, Q., Stankovic, J., Hendawi, A., Zhang, D., He, T., Pappas, G.J., 2017. Data-Driven Robust Taxi Dispatch under Demand Uncertainties. arXiv:1603.06263 [cs].

Nourinejad, M., Roorda, M.J., 2016. Agent based model for dynamic ridesharing. Transportation Research Part C: Emerging Technologies 64, 117–132. https://doi.org/10.1016/j.trc.2015.07.016

Ramezani, M., Nourinejad, M., 2018. Dynamic modeling and control of taxi services in large-scale urban networks: A macroscopic approach. Transportation Research Part C: Emerging Technologies, ISTTT22 94, 203–219. https://doi.org/10.1016/j.trc.2017.08.011

Wu, Y.H., Guan, L.J., Winter, S., 2008. Peer-to-Peer Shared Ride Systems, in: Nittel, S., Labrinidis, A., Stefanidis, A. (Eds.), GeoSensor Networks: Second International Conference, GSN 2006, Boston, MA, USA, October 1-3, 2006, Revised Selected and Invited Papers, Lecture Notes in Computer Science. Springer, Berlin, Heidelberg, pp. 252–270. https://doi.org/10.1007/978-3-540-79996-2_14

Zhu, P., Sirmatel, I.I., Trecate, G.F., Geroliminis, N., 2022. Idle-vehicle Rebalancing Coverage Control for Ride-sourcing systems, in: 2022 European Control Conference (ECC). Presented at the 2022 European Control Conference (ECC), pp. 1970–1975. https://doi.org/10.23919/ECC55457.2022.9838069