

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

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# Introduction



**Distributed Intelligence & Technology for Traffic & Mobility Management**

# DIT4TraM project

- **Distributed Intelligence & Technology for Traffic & Mobility Management**

- Horizon 2020 grant

- 2021 - 2024

- **Research topics :**

- On-demand services management

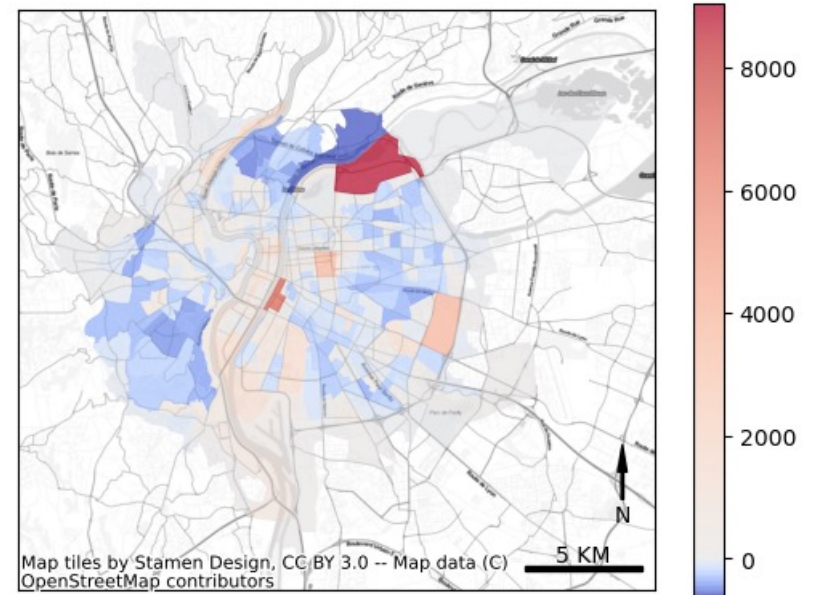
- Fleet rebalancing



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# Fleet rebalancing

- **Commuting patterns imply:**
  - Vehicles accumulation in attractive zones
  - Vehicles depletion in demanding areas
- **Supply / demand unbalance** leading to poor service performances
- Need for demand anticipation and vehicles proactive relocations



Accumulation and depletion patterns during a typical morning peak, Lyon, France

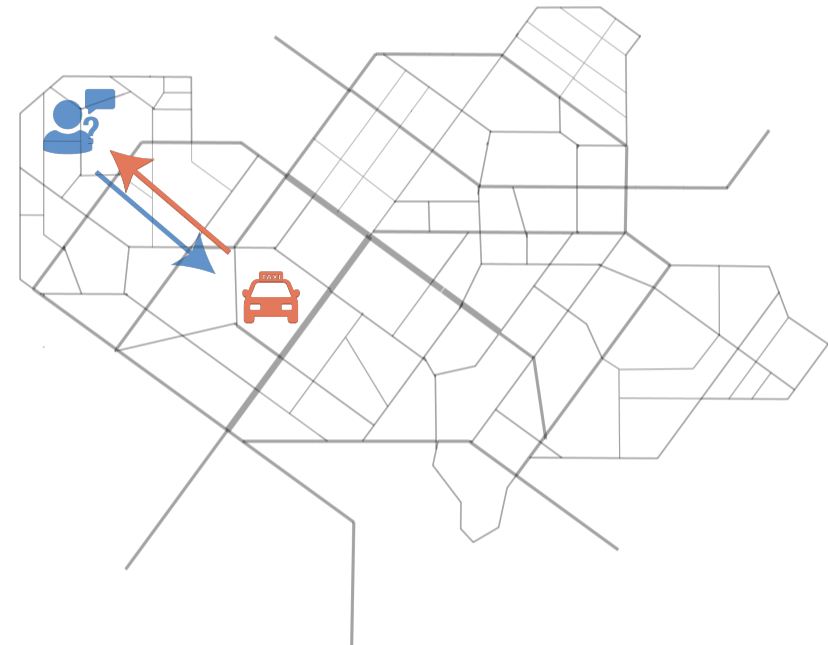
# Literature overview

- Various approaches – Pricing, information sharing, distributed coverage control, ...

- **Auctioning-based literature:**

- Wu et al., 2008
- Nourinejad et al., 2016
- Manjunath et al., 2021

-> Matching-focused approaches reacting to passengers' requests



# Methodology



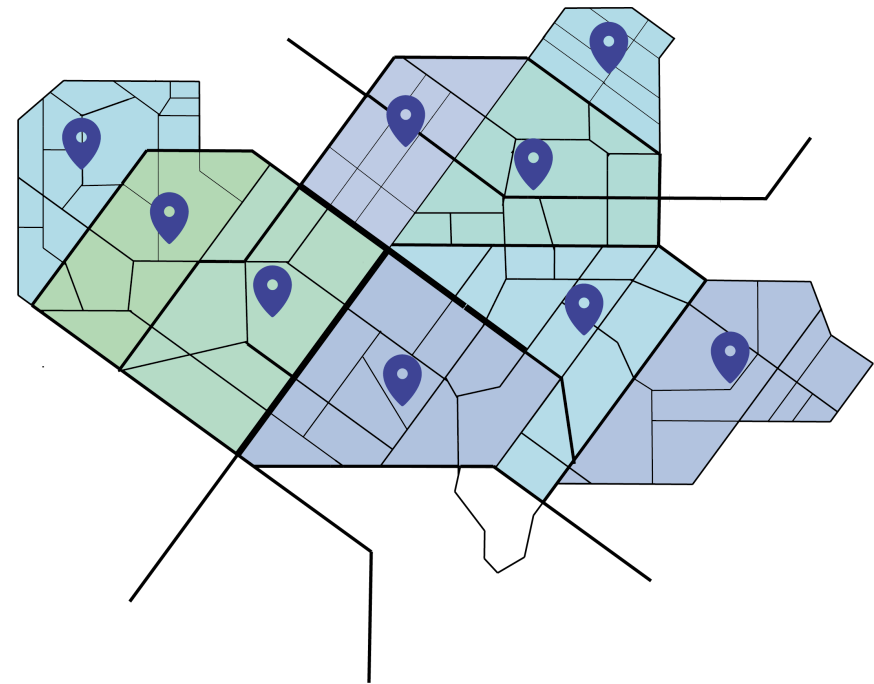
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# Proposed architecture

- **Multi-agent model including local controllers:**

1. Forecast demand
2. Emit relocation offers
3. Negotiate with vehicles

-> **Periodic rebalancing decisions taken in a two-sided matching market**

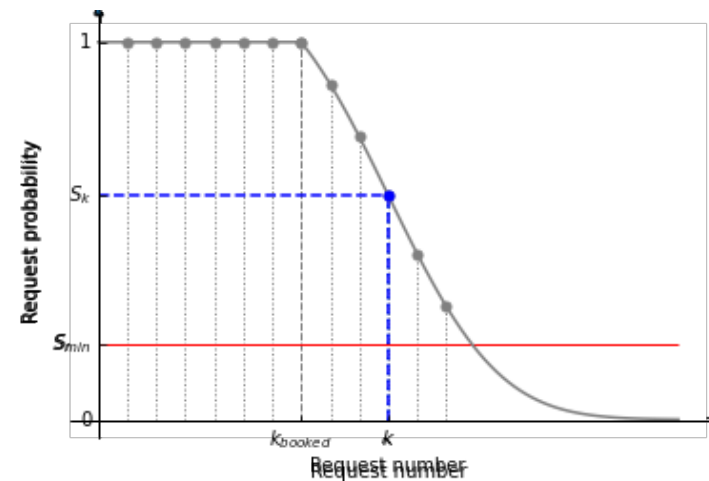


# Relocation offers

- **Offers definition**

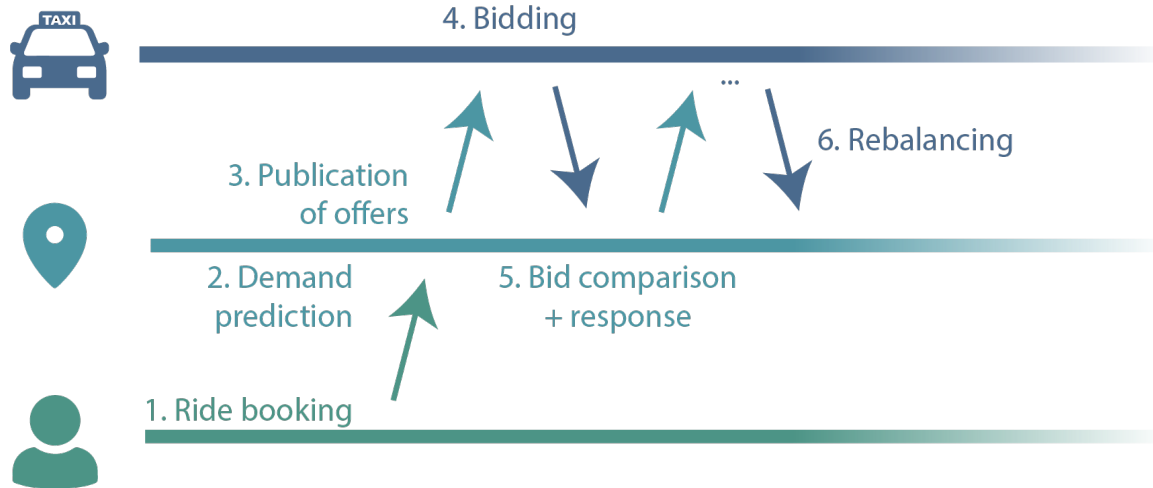
$$r_{i,T}^k = (p^k, \hat{g}_i)$$

- $p^k$ : request probability  
 $p^k = S_X(k) = P(X \geq k), \forall k \in N$
- $\hat{g}_i$ : gain expected from serving a passenger in region  $i$





# Rebalancing interface



- Drivers maximize their expected revenues
- Two-sided matching markets
- **Gale-Shapley algorithm(s)**
  - $u_v(r_i) = p^k \hat{g}_i - c_v^m d_{SP}(p_v, p_{r_i})$
  - no information centralisation
  - several matching iterations
- **Regions favour early vehicle arrival**
- **Distributed allocation of relocation offers**
- >  $u_{r_i}(p)$  decaying function of  $t_{SP}(p_v, p_{r_i})$

# Results



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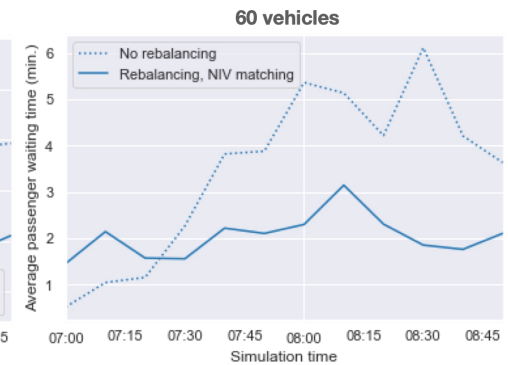
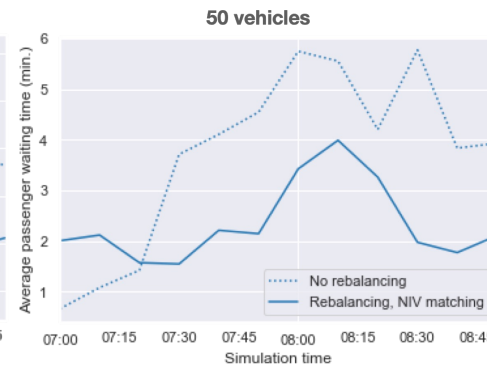
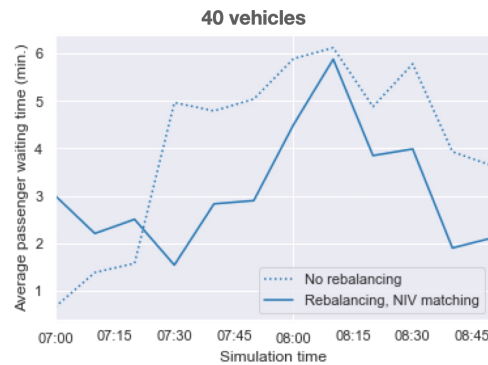
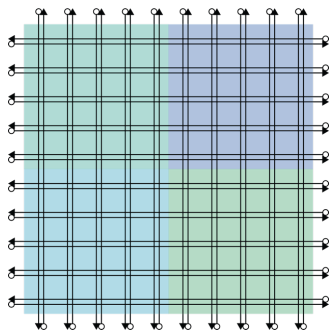
# Implementation & Case study 1

## MnMS open-source simulation platform

- Trip-based MFD traffic simulation core
- Mobility services simulation with vehicles and passengers tracking

## Case study 1 – Manhattan network

- Regular abstract network
- Theoretical dissymmetric demand peak
- Rebalancing assessment

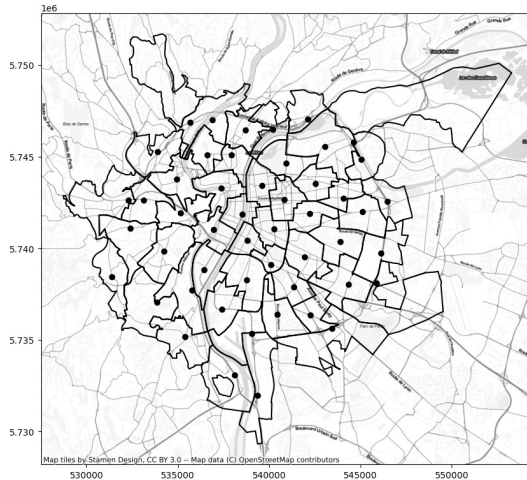


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# Case study 2 – Lyon, France

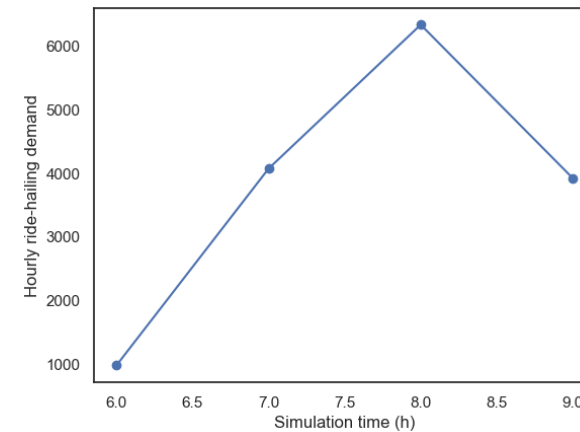
## Network

- Lyon major roads
- Zones generated as clusters of IRIS



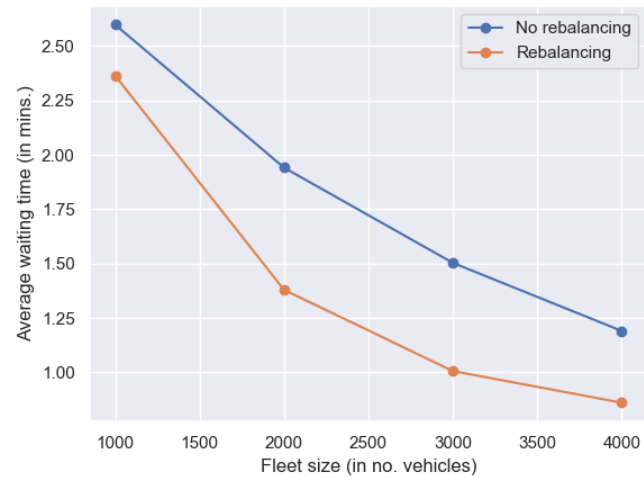
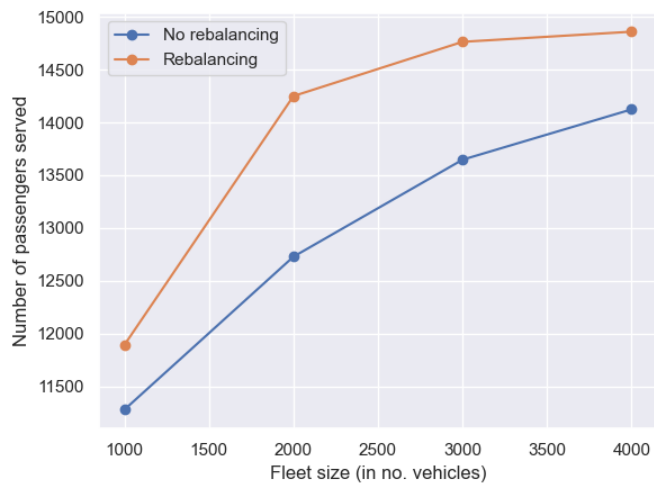
## Demand

- 4 hours of typical morning peak
- 15% of inner trips prioritize RH



# Service performances

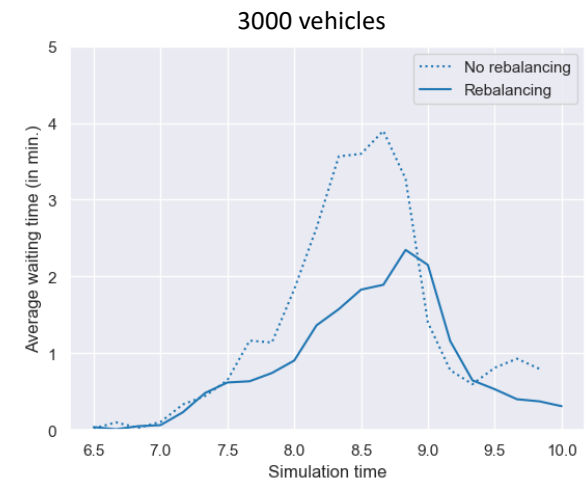
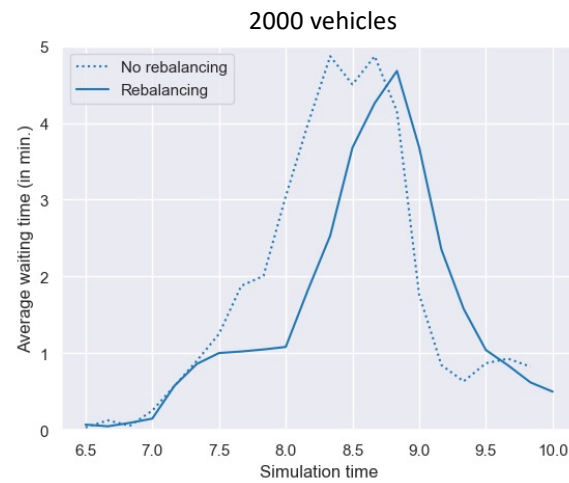
## Fleet size impact



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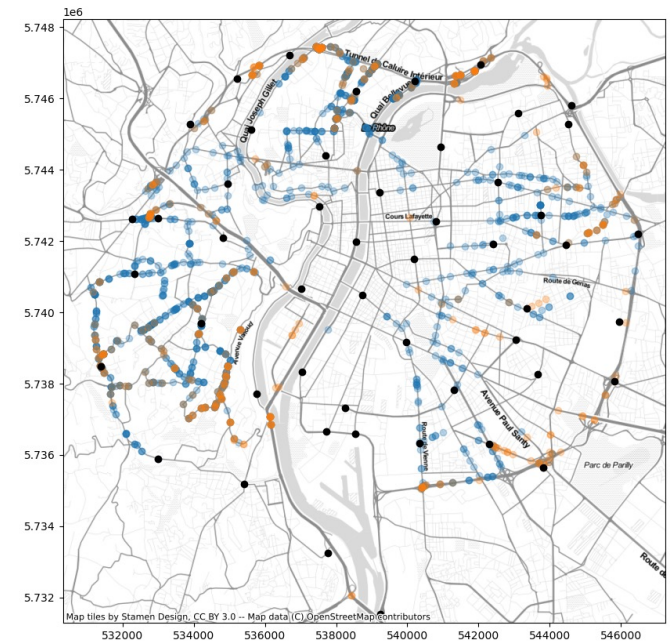
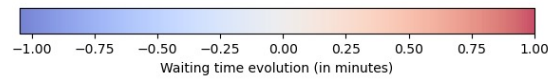
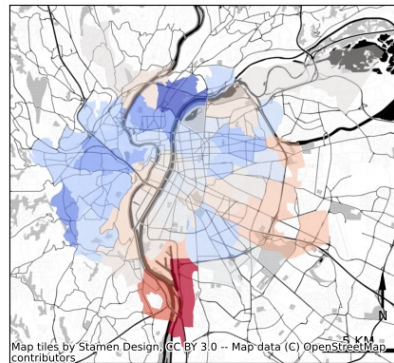
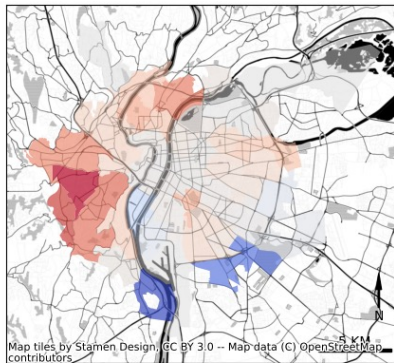
# Service performances

## Fleet size impact



# Service performances

## Spatial analysis



# Service performances

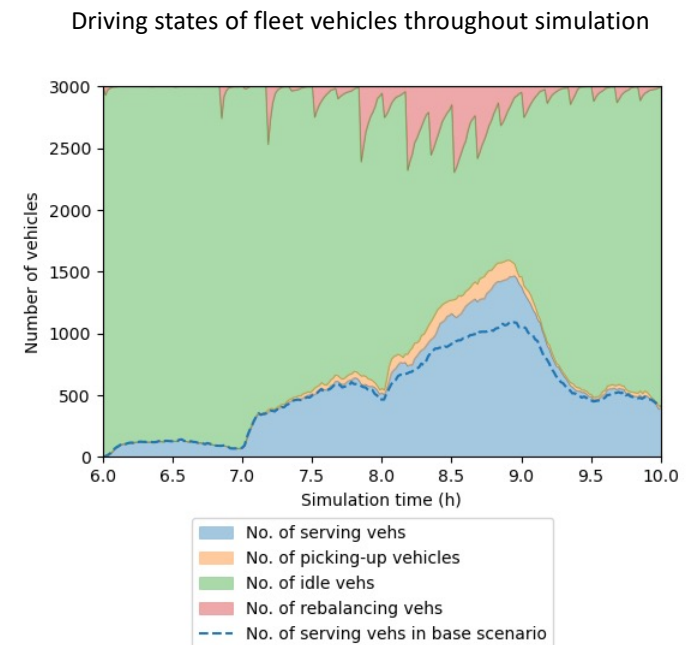
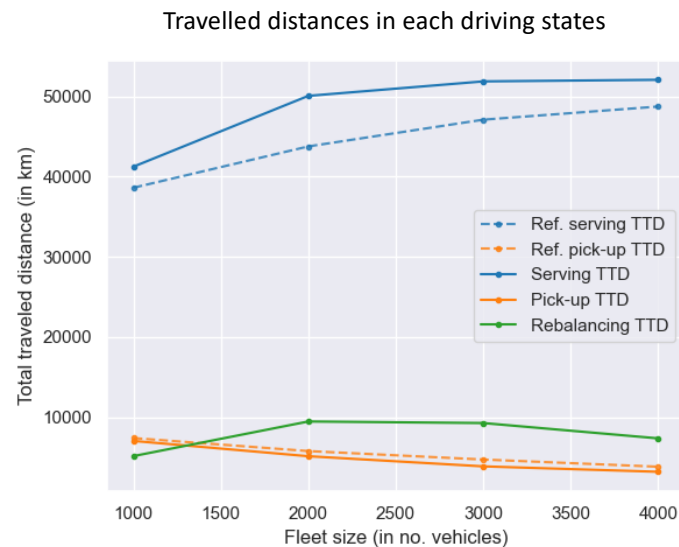
## Travelled distances

- Decrease in pick-up TTD
- Increase of service TTD
- But high repositioning distances

-> Locate depots to strategic network positions



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# Conclusion



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# Conclusion

## Current work

- Sensitivity analyses
- Impact of network design and depots locations

## Future research

- Extend to ride-splitting and multi-provider settings
- Enhance cooperation between zones
- Include user-/driver-intended incentives



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# References

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Nourinejad, M. and M. J. Roorda, *Agent Based Model for Dynamic Ridesharing*. Transportation Research Part C: Emerging Technologies, Vol. 64, 2016, pp. 117–132

Wu, Y. H., L. J. Guan, and S. Winter, *Peer-to-Peer Shared Ride Systems*. In *GeoSensor Networks: Second International Conference, GSN 2006*, Boston, MA, USA, October 1-33, 2006, Revised Selected and Invited Papers (S. Nittel, A. Labrinidis, and A. Stefanidis, eds.), Springer, Berlin, Heidelberg, Lecture Notes in Computer Science, 2008, pp. 252–270.37

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# Thank you!