



HAL
open science

AUCTION-BASED DISTRIBUTED RIDE-HAILING REBALANCING: THE CASE STUDY OF LYON, FRANCE

Manon Sepecher, Ludovic Leclercq

► **To cite this version:**

Manon Sepecher, Ludovic Leclercq. AUCTION-BASED DISTRIBUTED RIDE-HAILING REBALANCING: THE CASE STUDY OF LYON, FRANCE. TRB 2024, TRB, Jan 2024, Washington (DC), United States. hal-04700668

HAL Id: hal-04700668

<https://hal.science/hal-04700668v1>

Submitted on 25 Sep 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1 **AUCTION-BASED DISTRIBUTED RIDE-HAILING REBALANCING: THE CASE**
2 **STUDY OF LYON, FRANCE**

3
4
5

6 **Manon Seppecher***

7 Univ. Gustave Eiffel, ENTPE, Univ. Lyon, LICIT-ECO7
8 UMR_T 9401, F-69518, Lyon, France
9 Email: manon.seppecher@univ-eiffel.fr

10

11 **Ludovic Leclercq**

12 Univ. Gustave Eiffel, ENTPE, Univ. Lyon, LICIT-ECO7
13 UMR_T 9401, F-69518, Lyon, France
14 Email: ludovic.leclercq@univ-eiffel.fr

15

16 * Corresponding author

17

18 Paper submitted for presentation at the 103nd Annual Meeting Transportation Research Board,
19 Washington D.C., January 2024

20

21 Special call by ACP50 committee on "Traffic flow operations in large-scale urban networks"

22

23 Word Count: 5688 words + 5 table(s) × 250 = 6938 words

24

25

26

27

28

29

30 Submission Date: August 1, 2023

1 ABSTRACT

2 Ride-sourcing services offer cost-efficient, convenient, and flexible mobility solutions, making
3 them competitive compared to traditional transportation modes. However, these mobility services
4 must address various operational issues to remain attractive. One such challenge arises from fast-
5 changing asymmetric mobility patterns, leading to the accumulation of idle vehicles in attractive
6 zones and shortages of vehicles in other neighborhoods. As a result, passengers experience high
7 pick-up waiting times and abandonment rates. Based on demand anticipation, proactive fleet re-
8 balancing helps counteract the impact of demand patterns on fleet distribution and ensure service
9 continuity. In previous work, we developed a distributed rebalancing method based on negotiation
10 between vehicles and local controllers and analyzed its features on a small abstract network. This
11 paper further investigates the characteristics of the strategy on a larger scale using an actual urban
12 case study, the city of Lyon, France. Extensive sensitivity analyses are conducted, covering various
13 aspects such as user patience, fleet size, uncertainty, and depot locations, among others.

14

15 *Keywords:* fleet management, on-demand mobility, ride-hailing, distributed algorithms, multi-
16 agent modelling, demand uncertainty

1 INTRODUCTION

2 Urban environments are witnessing a remarkable diversification of mobility services, with innova-
3 tive offerings such as AI-powered ride-sourcing and vehicle sharing complementing and compet-
4 ing against conventional public transit systems. These services significantly expand transportation
5 options for urban dwellers and meet an increasingly dynamic and non-regular mobility demand.

6 In particular, e-hailing services grant urban residents enhanced flexibility and convenience.
7 Compared to public transit, they offer on-spot, on-demand, no-connection rides. Compared to
8 private car use, they are cost-effective and solve parking issues. These individual benefits extend
9 to the collective and environmental scale, as reducing car ownership relieves pressure on land
10 and the need for parking spaces. And while these services do contribute to congestion, mitigating
11 measures such as ride-splitting and limiting empty cruising behavior can address this drawback [1].

12 However, unlocking these benefits requires urban authorities and service operators to im-
13 plement effective service management strategies. Public authorities must regulate competition
14 between mobility services, which can lead to increased cruising distances [2]. Meanwhile, service
15 operators must successfully address various operational challenges, including demand prediction,
16 ride pricing, passenger-vehicle matching, vehicle routing, and fleet rebalancing.

17 Fleet rebalancing consists in providing relocating directions to idle vehicles. In doing so,
18 companies mitigate fleet shortages and prevent service gaps resulting from the large-scale urban
19 mobility dynamics and asymmetric patterns and consequent accumulation of end-of-travel vehicles
20 in attractive areas. A simple rebalancing strategy involves relocating idle vehicles to areas where
21 recent demand was unmet [3–5] have proposed approaches in this direction. However, these strate-
22 gies rely on past demand information and are reactive. Proactive strategies, based on future demand
23 knowledge or prediction, can achieve better performances. Numerous literature studies have de-
24 veloped proactive rebalancing strategies [6–9]. However, most offer centralized methods, raising
25 questions about scalability, robustness to system failures, and their suitability to model and manage
26 increasingly decentralized services, where self-employed drivers make their own decisions.

27 In this respect, distributed approaches are attractive alternatives. Recent works have looked
28 into fleet rebalancing through the lens of passengers and drivers-intended incentives, with pricing
29 and information-sharing strategies [10], coverage control [11] or auctioning [12]. In this latter
30 work, we proposed a strategy in which the relocation directions provided to drivers result from a
31 negotiation process with local controllers, which aim at attracting vehicles nearby. While auction-
32 ing approaches have previously been employed for developing reactive vehicle-passenger matching
33 strategies [9, 13, 14], this study was the first attempt, to our knowledge, to extend its application
34 to large-scale repositioning. In the present paper, we apply this methodology to a large-scale case
35 study in Lyon, France. We conduct extensive sensitivity analyses to passengers waiting time toler-
36 ance, fleet size, demand uncertainty, and depot locations. The results evidence convincing benefits
37 and provide guidelines for further improving the strategy.

38 This paper is organized as follows. Section 3 summarizes the key elements of the method-
39 ology. Section 4 presents the simulation platform and test case. Section 5 details our results.
40 Section 6 concludes this paper.

1 METHODOLOGY

2 Outline

3 We investigate the performance of a decentralized architecture for large-scale, e-hailing fleet re-
 4 balancing. In this setup [12], the rebalancing decision-making process is outsourced from ride-
 5 sourcing companies' management to a network of controllers that act on behalf of a public au-
 6 thority. The operating zone is partitioned into service areas, each managed by a local controller,
 7 supported by physical infrastructures (e.g., taxi stations, vehicle deposits, or parking lots).

8 Local controllers aim to ensure prompt pick-up in response to local ride-hailing demand.

9 To achieve this, they:

- 10 1. Forecast local ride-hailing demand.
- 11 2. Issue *relocation offers* accordingly.
- 12 3. Engage in negotiating with vacant vehicles to have them relocate within the service area
- 13 boundaries.

14 Local demand prediction enables controllers to estimate the number of vehicles required to
 15 meet the expected local demand. They periodically (e.g., every 10 minutes) engage in a distributed
 16 negotiation process with vehicles to attract the necessary number within their boundaries. This
 17 process is modeled as a two-sided matching market and accounts for both the regions and the
 18 vehicles' utilities. Once matched with a service area, vehicles relocate to the nearest vehicle depot
 19 of this area and wait for a match with a passenger there.

20 Since a decentralized public authority handles the rebalancing decisions, the method is
 21 suited for managing vehicles' rebalancing for multiple and competing ride-sourcing services. How-
 22 ever, this paper assumes a monopoly setting with a single company operating on the network. We
 23 also assume that vehicles and the ride-sourcing service comply with the rebalancing decisions.
 24 Future research may explore the model's properties in a competitive setting and with partially
 25 compliant vehicles or services.

26 The remaining of this section is organized as follows. Section 3.2 presents how the demand
 27 prediction allows to anticipate local needs for vacant vehicles and to prepare the negotiation phase.
 28 Section 3.3 presents the negotiation process. Section 3.3 defines the regional and vehicle utility
 29 applied in this paper.

30 Relocation offers

31 Local controllers issue relocation offers as a vector of information and attraction to vacant vehicles.
 32 Let i denote a service area and T a rebalancing period. For all k in \mathbb{N}^* , we define the k^{th} relocation
 33 offer to region i and period $T + 1$ as $r_k = (p_k, \hat{g}_i)$, with:

- 34 • p^k the probability of observing at least k ride requests in i during T ;
- 35 • \hat{g}_i the expected income from serving the corresponding potential passenger, assumed to
 36 be independent of time.

37 Therefore, with relocation offers, local controllers communicate to drivers the likelihood of
 38 being matched with a passenger if they relocate in the region i and the revenue drivers can expect
 39 from such a relocation.

40 The analysis of historical data supports the estimation of those two features. On one side,
 41 analyzing the historical requests data allows us to characterize the ride-hailing demand probability
 42 distributions and estimate p^k . Conversely, \hat{g}_i can be derived from historical trip data. Based on
 43 this information, vehicles evaluate and compare their utility in relocating towards one region or the

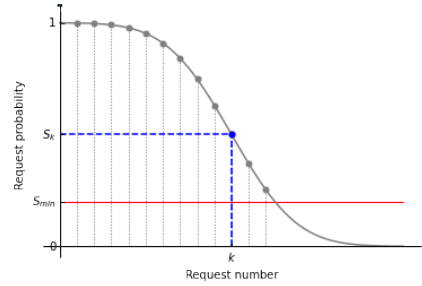


FIGURE 1: Definition of requests probability occurrences given the demand zonal distribution

1 other, sort their favorite relocation options and bid accordingly.

2 In theory, local controllers can emit an infinite number of relocation offers (each associated
 3 with a decreasing probability) and let the vehicles decide whether to apply or not on them. In
 4 practice, for realism and computational cost issues, local controllers only emit associated with an
 5 occurrence probability exceeding a minimum threshold p_{min} (set to 0.2 in this study). Figure 1
 6 illustrates partitioning the predicted future demand into uncertain requests.

7 **Vehicle-to-Controller negotiation scheme**

8 The periodic auctioning process is based on the distributed Gale-Shapley algorithm[15–17]. We
 9 summarize below the outline of our algorithm:

- 10 • Local controllers predict the future local demand (*potential future passengers*), and de-
 11 duce their future vehicle needs from it. They express those needs by publishing *relocating*
 12 *options* into a virtual two-sided *relocating market*. Each relocating option is associated
 13 with the likelihood that the demand will occur.
- 14 • With a fixed frequency, vacant vehicles enter the market and evaluate their utility for
 15 each relocating option. Vehicles estimate this utility by considering their relocation costs
 16 towards the service area, the likelihood of the demand associated with the relocating
 17 options, and the incomes expected for serving this demand. On this basis, the vehicles
 18 make an ordered list of the relocation options they consider useful and bid on the first.
 19 When bidding, vehicles declare their expected arrival time at their destination.
- 20 • Local controllers agents gather the bids of vehicles and evaluate the utility expected from
 21 the vehicle service, *i.e.*, the ability of the bidding driver to relocate on time for the an-
 22 ticipated demand. The local controller accepts the best vehicle’s bid for each anticipated
 23 passenger and rejects the others. A region having previously accepted a vehicle bid can
 24 reject it if it receives a more appealing offer at a successive matching round.

25 The process keeps on; rejected vehicles apply to their next favorite relocation offer until
 26 running out of interesting options. This process is illustrated in Figure 2.

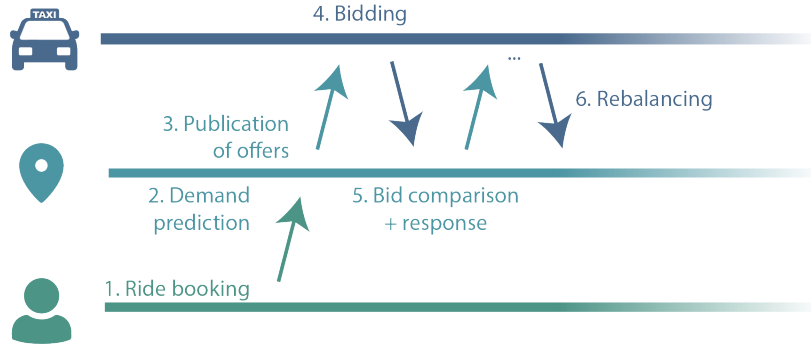


FIGURE 2: Communication protocol

1 Utility functions

2 Different utility functions can be envisioned here, but we focus at this stage on one function per
3 agent.

4 Utility of vehicles

5 Vehicles compute their utility $U_v(i, k)$ in relocating towards region i to serve potential passenger k
6 as the net profit of the rebalancing, *i.e.* as the difference between their expected earning $g(i, k)$ and
7 the relocating costs $c_{rebalancing}(v, i)$:

$$U_v(i, k) = g(i, k) - c_{rebalancing}(v, i) \quad (1)$$

$$= \bar{g}_i \cdot p^k - c_v^{km} \cdot d_{SP}(v, i) \quad (2)$$

8 The expected earnings are estimated from the relocation offer features as the product of
9 the ride-request occurrence with the average earnings when serving a passenger in the area. The
10 rebalancing costs are computed as the product of the vehicle empty kilometric cost c_v^{km} with the
11 relocating distance, computed as the shortest path between vehicle position v and the depot of the
12 region i .

13 Utility of local controllers

14 Local controllers gather simultaneously and independently the applications of vehicles to the vari-
15 ous relocation offers they published. Their utility is a decaying function of the travel time vehicles
16 need to relocate. Therefore, given two vehicles applying to the same relocation offer, the one clos-
17 est to the region depot will benefit the local controller more. On one side, it ensures the vehicle's
18 fast arrival and quick passenger pick-up. From a more global point of view, this utility setting
19 limits the empty mileage of vehicles.

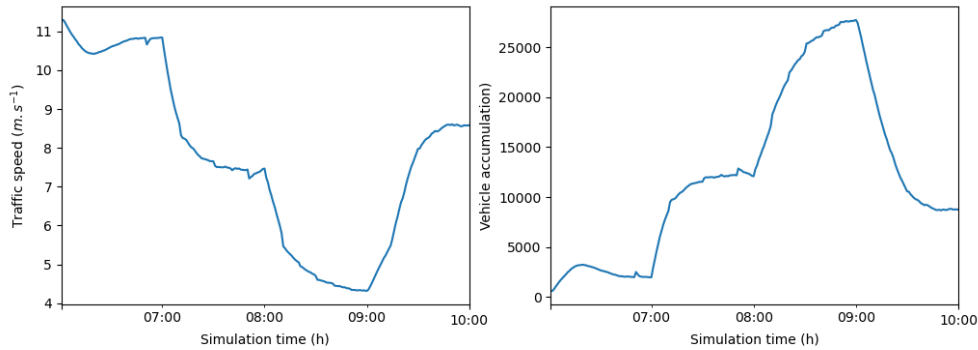


FIGURE 3: Traffic dynamics throughout a simulation

1 SIMULATION PLAN AND ENVIRONMENT

2 Simulation platform

3 We conduct an extensive simulation-based analysis in the open-source Python simulation platform
 4 MnMs (Multi-modal Network Modeling and Simulation) [18]. The platform relies on a multi-
 5 modal trip-based MFD (Macroscopic Fundamental Diagram) traffic model [19, 20]. It supervises
 6 the movements of vehicles and users over the network, applying the same collective mean speed
 7 per mode and urban region. Figure 3 illustrates the accumulation and dynamic speed profiles
 8 during one simulation. The platform includes a fleet management component that models different
 9 mobility services, such as individual modes, public transportation, and ride-sourcing (including
 10 ride-hailing and ride-splitting). For ride-sourcing services, the platform allows customization of
 11 default ride-sourcing management strategies addressing fleet dispatching and rebalancing issues.

12 Case study definition

13 *City specific features and demand balance*

14 The city of Lyon, France, is selected as a case study. Lyon is the third most populated city in
 15 France and the center of France's second most populated urban area. Figure 4 represents at a fine
 16 scale the neighborhoods of Lyon with inflow/outflow unbalance during the morning peak (6 am to
 17 10 am), considering flows emitted from the city center and outer suburbs not represented on the
 18 map. This representation allows us to identify the geographic patterns of the demand during that
 19 period and anticipate the need for fleet rebalancing when operating a ride-sourcing service. Some
 20 specific areas are characterized by large imbalances of incoming and outgoing flows, with high
 21 inflows and low outflows. It is especially the case for university areas: La Doua campus in the
 22 north of the city and Université Lyon 3 campus along the Rhône River. The area of the train station
 23 Lyon Part-Dieu, in the city center, and the Vinatier hospital area, in the eastern part of Lyon, also
 24 seem equally attractive. To a lesser extent, other regions of Lyon, such as the southern industrial
 25 neighborhoods, attract morning flows. Although these spatial demand patterns characterize private
 26 car users, they illustrate how ride-sourcing vehicles operating a similar demand are likely to get
 27 accumulated within that area if no rebalancing strategy is implemented.

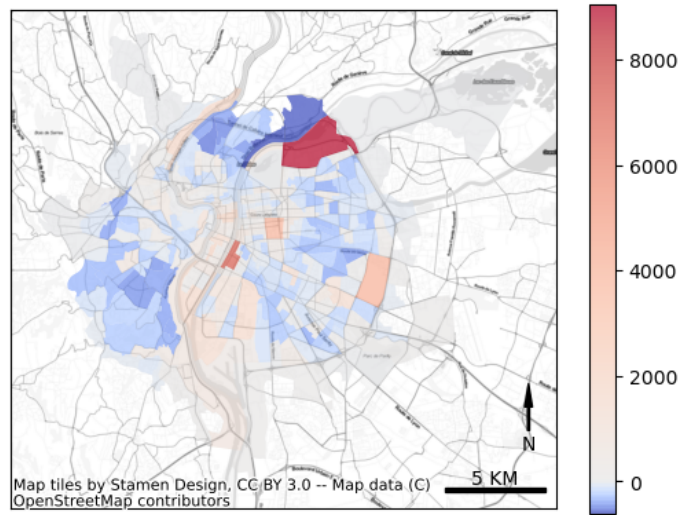


FIGURE 4: Travelers inflow and outflow during the morning peak

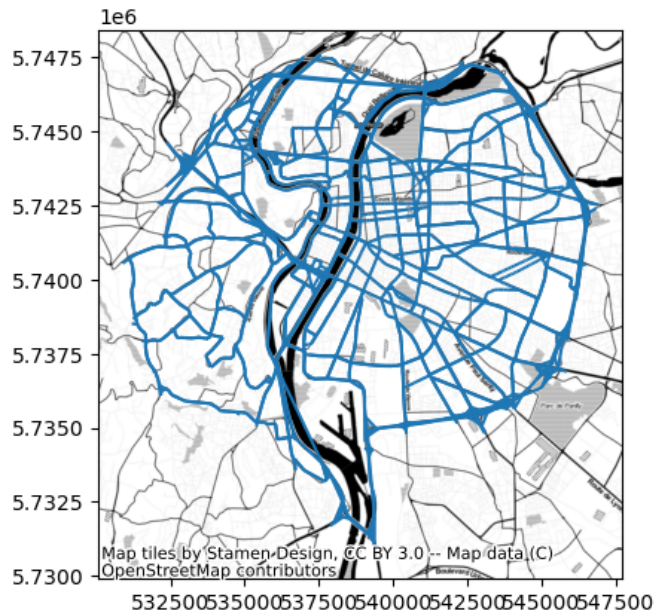


FIGURE 5: Simulation network: major road sections of Lyon, France

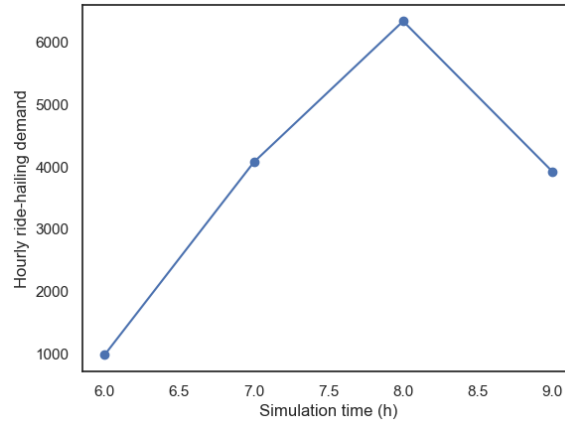


FIGURE 6: Overall ride-hailing demand

1 Simulated network

2 The simulated network covers 121 square kilometers and includes the city of Lyon and the city
 3 of Villeurbanne, both located within the main circular ring road. In order to conduct rapid simu-
 4 lations, we model the traffic on a simplified network of the city, made of highways, primary and
 5 secondary road sections only. The corresponding network is illustrated in Figure 5. This simpli-
 6 fied network version comprises 5586 links and 3605 nodes for a total link length of 542 km. The
 7 supply (MFD) calibration and the demand (discussed hereafter) were previously computed within
 8 the ERC Magnum Project [21].

9 Demand scenario

10 In this work, we simulate 4 hours of road traffic, representing the 4 hours of typical morning peak,
 11 between 6 and 10 am. The demand scenario defines individuals willing to travel from an origin to a
 12 destination at a given time while prioritizing one transportation mode (private car or ride-hailing).
 13 Stochastic demand scenarios are elaborated based on a dynamic hourly origin-destination matrix
 14 describing the trips in the city of Lyon and its urban area for a typical day. The spatial granularity of
 15 the OD matrix corresponds to the IRIS (reference spatial division of the French statistical institute)
 16 zoning. Individual demand is generated by sampling origin and destination uniformly amongst
 17 nodes of the origin and destination IRIS zones and sampling departure time with a Poisson process.
 18 We additionally assign 15% of internal flows to ride-hailing mode, with the remaining users using
 19 private cars instead. The temporal hourly profile of the resulting ride-hailing demand is plotted in
 20 Figure 6.

21 Service areas and depots locations

22 We partition the city into 50 service areas to support implementing our rebalancing strategy. The
 23 partitioning is derived from a K-Means clustering of the IRIS zoning of the city. It is illustrated
 24 in Figure 7. Each service area is managed by a local controller and associated with one or several
 25 depots. We call *well-connected nodes* nodes located at road intersections with at least two different
 26 downstream directions. To study the effect of depot locations, we explore five different depot
 27 scenarios, illustrated in Figure 8, and defined as follows:

- 28 • Scenario 1: Each service area contains a single depot located at a random well-connected

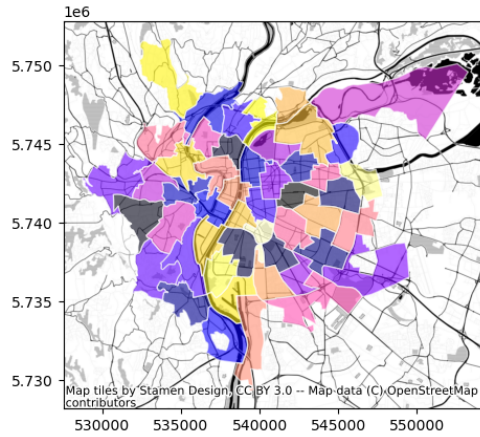


FIGURE 7: Partitioning of Lyon into 50 demand zones

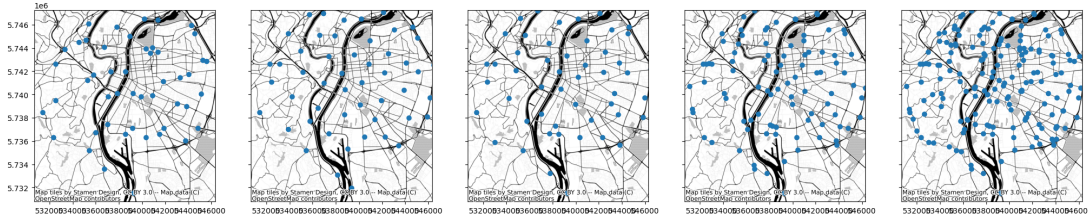


FIGURE 8: Different scenarios of depots locations

- 1 node of the area;
- 2 • Scenario 2: Each service area contains a single depot located at the centroid node of the
- 3 area;
- 4 • Scenario 3: Each service area contains a single depot located at the closest well-connected
- 5 node from the centroid of the area;
- 6 • Scenario 4: Each service area contains up to 3 depots, one located as in scenario 3, the
- 7 others located at random well-connected nodes;
- 8 • Scenario 5: Each service area contains up to 5 depots, one located as in scenario 3, the
- 9 others located at random well-connected nodes.
- 10 located at the centroid of the region.
- 11 Scenario 3 is the default depot mesh scenario used for all other sensitivity analyses.

12 **Simulation settings**

13 At the beginning of the simulation, all vehicles are empty and idling and uniformly distributed
 14 on the network. The auctioning and rebalancing period is fixed at 10 minutes. After rebalancing,
 15 vehicles are available for matching. Requesting passengers are matched with the nearest available
 16 vehicle.

17 The ride pricing scheme c_{ride} is designed as the sum of a fixed service cost $c_{service}$ and a
 18 mileage fare applied to the shortest path distance between the pick-up and drop-off point:

Parameter		Unit	Values
Ride-sourcing fleet size	M	vehicles	{1000, 2000, 3000 , 4000}
Maximum matching time	δ_{match}	minutes	1
Max. waiting time before service abandonment	$\delta_{pick-up}$	minutes	{ 5 , 10}
Rebalancing frequency	Δ_r	minutes	10
Solo trip base fare	f_{base}	€	2.20
Solo trip per-km fare	f_{km}	€/km	1.00
Empty per-km cost	$c_{s,v}$	€/km	{ 0.5 , 1, 2, 3, 4}
Demand prediction uncertainty	$\tilde{\sigma}$.	{ 0.1 , 0.2, 0.3}
Request probability mean threshold	p_{min}	.	0.2

TABLE 1: Simulation parameters

$$f_{ride}(p_o, p_d) = f_{base} + f_{km} \cdot d_{SP}(p_o, p_d) \quad (3)$$

1 Table 1 summarizes the parameters used in this paper. Bold parameters used within param-
 2 eter ranges indicate the default values.

3 Simulation plan and Key Performance Indicators (KPIs)

4 The result section successively explores the performance of the rebalancing strategy and its sensi-
 5 tivity to:

- 6 • different passenger patience tolerance scenarios;
- 7 • different fleet size scenarios;
- 8 • demand uncertainty and rebalancing costs;
- 9 • various depot locations strategies.

10 In those studies, the performance of the service is systematically analyzed through the
 11 scope of quality of service (number of passengers served and waiting time) and vehicle activities
 12 (idle time and vehicle traveled distance per served passenger).

13 RESULTS

14 Overall performances in various passengers waiting tolerance settings

15 Service performances

16 We compare the service performances with and without implementing the fleet rebalancing. The
 17 waiting time tolerance of passengers $\delta_{pick-up}$ is expected to impact each strategy's results signifi-
 18 cantly. Therefore, we compare the results in two settings, $\delta_{pick-up} = 5$ minutes and $\delta_{pick-up} = 10$
 19 minutes. Table 2 gathers the performance of each strategy in terms of the number of passengers
 20 served and passengers' average waiting time before pick-up. The table also records these perfor-
 21 mances for the whole simulation time (6 am to 10 am) and the peak hour only (8 am to 9 am). We
 22 make the following observations.

- 23 • First, in both waiting tolerance settings, the rebalancing strategy successfully contributes
 24 to increasing the number of passengers served and reducing the waiting time.
- 25 • Second, the peak hour particularly benefits from the rebalancing strategy implementation,
 26 with more significant passenger increases and waiting time drops.
- 27 • Finally, the increase in passengers served is stronger for $\delta_{pick-up} = 5$ minutes (+18.41%
 28 during peak hour) than for $\delta_{pick-up} = 10$ minutes (+4.80%). Instead, the waiting time

		5 minutes				10 minutes			
		Reference	Rebalancing	Abs	Rel (%)	Reference	Rebalancing	Abs	Rel (%)
No. served passengers	Global	13,647.00	14,764.00	1,117.00	8.18	14,837.00	15,121.00	284.00	1.91
	Peak hour	4,996.00	5,916.00	920.00	18.41	5,940.00	6,225.00	285.00	4.80
Waiting time (in min.)	Global	1.50	1.01	-0.50	-33.07	2.11	1.27	-0.84	-39.90
	Peak hour	2.35	1.56	-0.79	-33.72	3.63	1.93	-1.70	-46.74

TABLE 2: Service performance comparison with different passengers waiting time tolerance

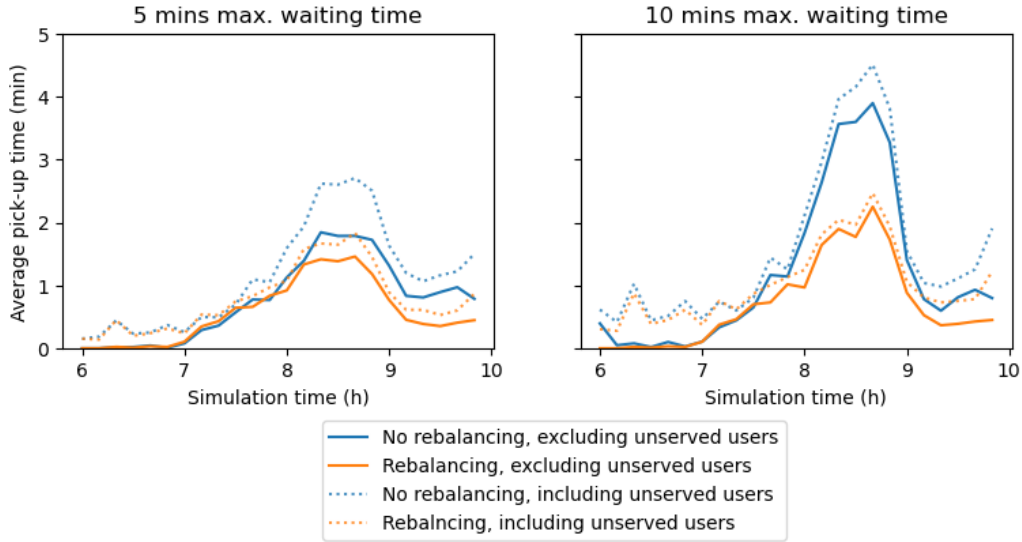


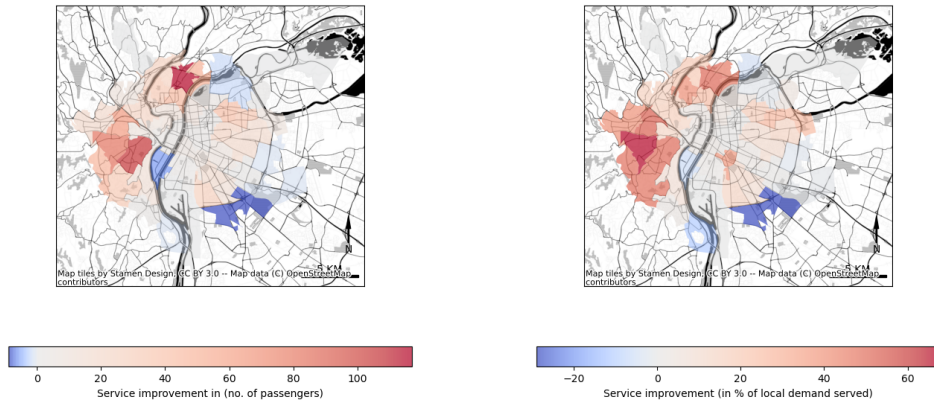
FIGURE 9: Waiting time evolution through simulation in both waiting tolerance settings

1 reduction is more significant if $\delta_{pick-up} = 10$ minutes (-1.70 minutes) rather than if
 2 $\delta_{pick-up} = 5$ minutes (-0.79 minutes).

3 This observation highlights two aspects of the benefits of a rebalancing strategy. On the one
 4 hand, under tight time constraints, fleet rebalancing enables the service to reduce abandonment by
 5 serving additional passengers. However, the pick-up time windows are such that the waiting time
 6 cannot be significantly reduced. When passengers are more patient, the service without rebalancing
 7 already meets demand satisfactorily. Nevertheless, rebalancing can still boost service quality by
 8 reducing passengers' pick-up times.

9 Figure 9 displays the evolution of passengers pick-up waiting throughout the simulation
 10 for each waiting time tolerance setting. The *no rebalancing* strategy is represented in blue lines,
 11 and the rebalancing strategy is in orange. The solid lines represent the average waiting time for
 12 served passengers only, while the dotted lines correspond to waiting time, including unserved
 13 passengers. The plots confirm that the passengers' waiting time reduction is especially significant
 14 when passengers are patient. In both cases, the rebalancing strategy limits the waiting time increase
 15 during the peak. Plus, considering all users, fleet rebalancing delays the waiting time increase and
 16 ensures a faster recovery.

17 The remaining analyses of this paper have been conducted with a waiting tolerance $\delta_{pick-up} =$
 18 5 minutes.



(a) Map of the service evolution in number of additional local passengers served (b) Map of the service evolution in percentage of local demand served

FIGURE 10: Zonal service improvement in number of passengers served

1 *Spatial performances*

2 In this section, we analyze the service performance at a finer scale. Figure 10 illustrates the spatial
 3 distribution of the zonal increase of passengers served. Figure 10a displays its absolute evolution.
 4 Instead, Figure 10b represents the extra share of local demand served with rebalancing.

5 Regarding the absolute increase of demand served, the rebalancing strategy is especially
 6 beneficial to a few neighborhoods in the western and northern parts of Lyon. These neighborhoods
 7 are characterized by a reduced-density road network (cf. Figure 5) due to hilly relief and mainly
 8 residential land use. When looking at the extra share of local demand satisfied, the results are less
 9 contrasted, and many neighborhoods appear to benefit from the fleet rebalancing, allowing to serve
 10 an extra 60% of the local demand. The areas benefiting the least or suffering from the rebalancing
 11 strategy correspond to areas likely to face vehicle accumulation in Figure 4.

12 Passenger waiting times are also analyzed with this granularity and displayed in Figure 11.
 13 The map evidences a uniform decrease in waiting time in the western and northern areas of Lyon
 14 and the city center. Concerning waiting time, the southern service area suffers the most from the
 15 strategy implementation. As the demand in this area is minimal, the variation of service for users
 16 there strongly impacts the local service perception.

17 Finally, Figure 12 represents the locations of unserved passengers. The rebalancing strategy
 18 succeeds in drastically reducing the number of unserved positions. However, some service gaps
 19 subsist, with well-defined areas concentrating on the frequently unserved positions. For some
 20 neighborhoods (cf. in the southwest of the city), it is due to the distance from the nearest depots.
 21 For some others (cf. in the south-east of the city), the location of nearby depots does not prevent
 22 a high density of unserved requests. It is a consequence of working with a directed network and
 23 occurs when depots are located downstream of the demand. Then, the vehicles are relocated to the
 24 depots to serve this local demand but later fail in serving it because it implies significant detours
 25 and pick-up times. Vehicles from other nearby depots may answer the matching request instead,

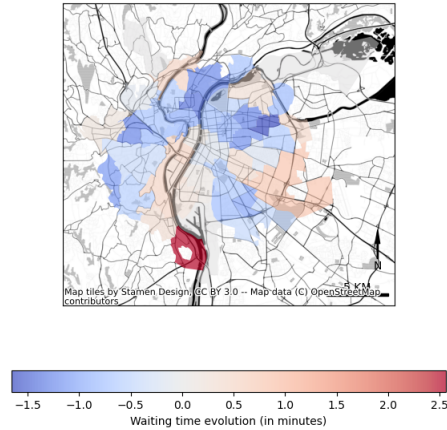


FIGURE 11: Map of zonal average waiting time reduction

- 1 leading to vehicles shortage in those depots and propagating demand dissatisfaction.
- 2 This limit of the approach and sensitivity to depot location is explored later in this paper.

3 *Vehicles activities*

- 4 Looking into the rebalancing impact on vehicle activities, Figure 13 illustrates the states of the
- 5 ride-hailing fleet throughout the simulation. Compared to the *no rebalancing* strategy, the periodic
- 6 rebalancing of vehicles significantly increases the number of in-service vehicles during the demand
- 7 peak. However, we observe that a share of rebalancing vehicles does not systematically translate
- 8 into a similar increase in serving vehicles. The demand uncertainty and situations of depots located
- 9 downstream of the demand partially explain this observation, which needs further investigation.
- 10 During the peak, due to the travel time increase, relocating vehicles are still traveling when the
- 11 next rebalancing period start. It may result in vehicles arriving too late into the next rebalancing
- 12 period and missing the passenger they were relocating for, contributing to "failed" relocations.
- 13 Sensitivity to rebalancing frequency is not explored in this work, but this aspect will be studied in
- 14 future work to evaluate how it alters service performances.

- 15 Table 3 summarizes the numerical values of some key indicators to evaluate the activities of
- 16 vehicles, as they could be considered proxies for the drivers' revenue estimation. With no surprises,
- 17 since the number of passengers served rises, the average idle time (*i.e.*, the time when vehicles are
- 18 neither picking-up nor serving a passenger) of vehicles decreases significantly. However, the ve-
- 19 hicle traveled distance per passenger increases significantly, meaning that the rebalancing strategy
- 20 inflicts additional empty distance for serving passengers compared to the *no rebalancing* strategy.
- 21 This result is further discussed in the next section.

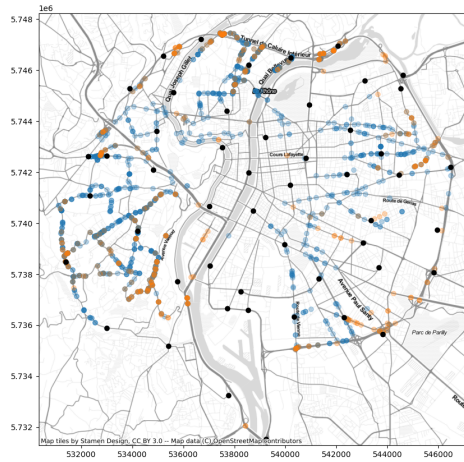


FIGURE 12: Spatial distribution of unserved users, without rebalancing (in blue) and with rebalancing (in orange). The black dots represent the depots locations.

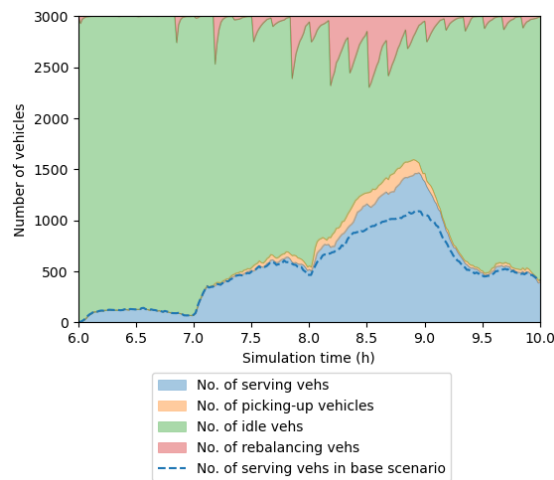


FIGURE 13: Distribution of the activities of vehicles throughout simulation time

	Reference	Rebalancing	Abs	Rel (%)
Avera idle time (min)	64.88	58.38	-6.50	-10.02
Average traveled distance per served passenger (km)	3.80	4.41	0.61	16.00

TABLE 3: Comparison of vehicles activity indicators

	Number of passengers				Waiting time (mins)			
	Reference	Rebalancing	Abs	Rel (%)	Reference	Rebalancing	Abs	Rel (%)
1000	11278.00	11891.00	613.00	5.44	2.60	2.36	-0.23	-9.02
2000	12728.00	14250.00	1522.00	11.96	1.94	1.38	-0.56	-28.93
3000	13647.00	14764.00	1117.00	8.18	1.50	1.01	-0.50	-33.07
4000	14124.00	14860.00	736.00	5.21	1.19	0.86	-0.33	-27.69

TABLE 4: Sensitivity of service performances to fleet size

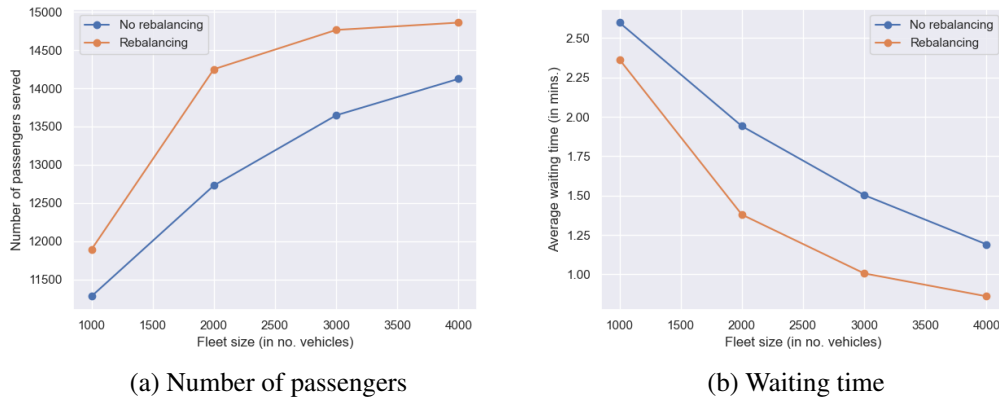


FIGURE 14: Sensitivity of service quality to fleet size

1 **Sensitivity to fleet size**

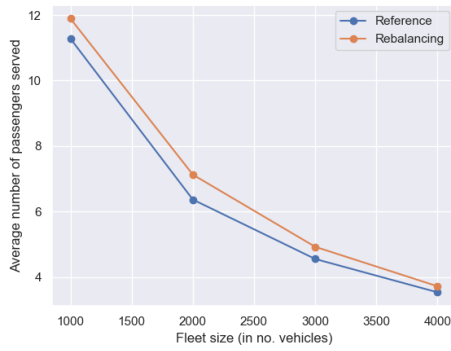
2 *Service performances*

3 The effect of fleet size on service quality is assessed and displayed in Table 4 and Figure 14.
 4 Figure 14a illustrates the effect of the rebalancing strategy on the number of passengers served.
 5 Instead, Figure 14b displays the effect of the rebalancing strategy on the number of passengers
 6 served. The rebalancing strategy is shown to have the most significant impact with the middle fleet
 7 scenarios (2000 and 3000 vehicles). These scenarios provide a large fleet with vacant vehicles
 8 available for rebalancing but limited enough to require rebalancing. The 2000-vehicles scenario
 9 provides the highest service quality increase in passengers (+11.96%). Instead, the 3000 vehicles
 10 scenario ensures the highest waiting time reduction (-33.07%).

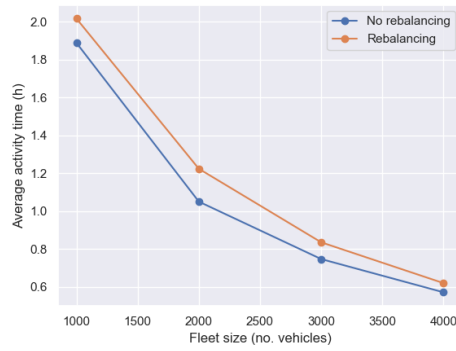
11 *Vehicle activities*

12 Extending the analysis carried on in the previous section, we look into the impacts of fleet size and
 13 rebalancing on vehicle activities. While the rebalancing strategy allows serving more passengers
 14 per vehicle, the increase in fleet size significantly counteracts this effect (Figure 15a). The activity
 15 time of vehicles follows similar trends (Figure 15b).

16 Looking into equity indicators, the rebalancing strategy is also shown to reduce inequities
 17 between vehicles. Figure 16 displays for instance the interdecile ratio $\frac{D_8}{D_2}$ and difference between
 18 $D_8 - D_1$. Except for the more extensive fleet, the rebalancing strategy reduces the relative and
 19 absolute difference between the most and least active vehicles of the fleet.

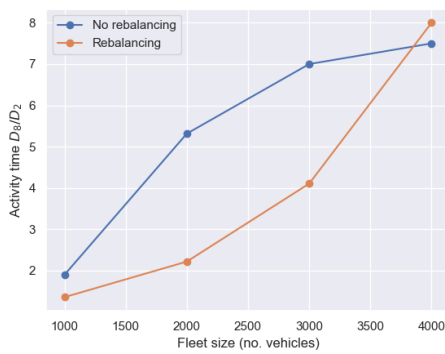


(a) Average no. passengers served per vehicle

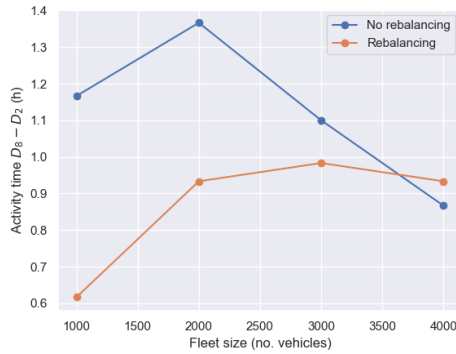


(b) Vehicle idle time reduction

FIGURE 15: Sensitivity of vehicles paid activities to fleet size

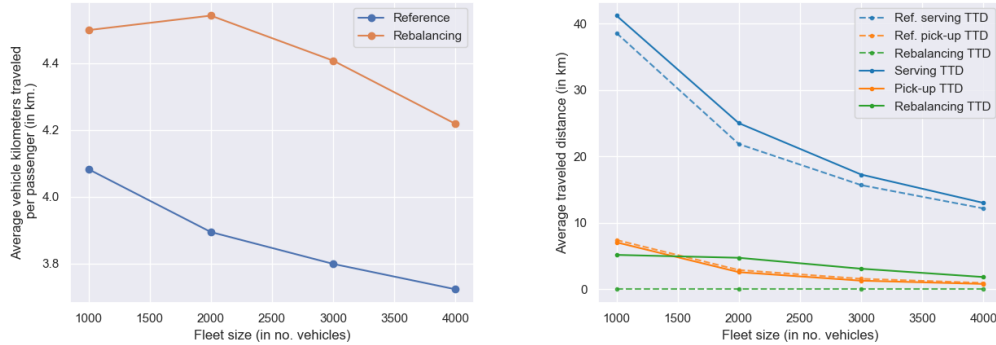


(a) Average no. passengers served per vehicle



(b) Vehicle idle time reduction

FIGURE 16: Sensitivity of vehicles paid activities to fleet size



(a) Vehicle traveled distance per served passenger (b) Contributions of service activities to average traveled distances

FIGURE 17: Evolution of traveled distances with fleet size

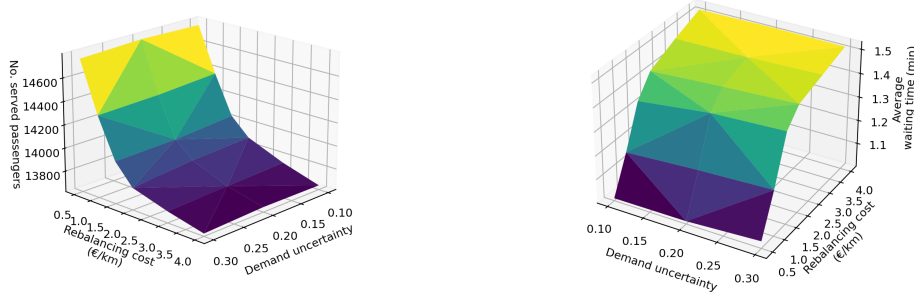
1 However, as illustrated in Figure 17a, the rebalancing strategy implies a general increase in
 2 the average distance vehicles travel per passenger. Figure 17b details the total distances traveled per
 3 activity. As the number of passengers served increased with rebalancing, the distances traveled for
 4 service also increased. The rebalancing strategy slightly decreases the pick-up distances, meaning
 5 that vehicles located at depots are, on average, closer to customers than without fleet rebalancing.
 6 However, the new rebalancing distances largely counteract this pick-up distance decrease.

7 Several factors can explain this significant extra travel distance:

- 8 • First, when vehicles rebalance, they head to the region depot before traveling from the
 9 depot to the passenger’s pick-up location. This results in extra distances compared to a
 10 direct pick-up.
- 11 • Second, as the network is sparse and directed, the shortest paths from the vacant vehicle
 12 position to the depot and from the depot to the pick-up position imply detours and over-
 13 estimated traveled distance compared to the actual network. Densifying the depots’ mesh
 14 or optimizing their location can contribute to reducing this additional distance.
- 15 • Finally, possible mismatches in the rebalancing process due to demand uncertainty may
 16 result in unsuccessful rebalancing for drivers, requiring them to relocate again.

17 Sensitivity to demand uncertainty and rebalancing costs

18 This section explores the joint effect of demand uncertainty and rebalancing costs on service per-
 19 formances. On the one hand, the higher the demand uncertainty, the more relocation offers are
 20 published, but with reduced occurrence probabilities, making them less attractive for vehicles.
 21 On the other hand, relocating costs also impact the vehicle rebalancing utility (cf. Equation 2).
 22 We explore uncertainty levels ranging from 10 to 30% of the mean demand, and the rebalancing
 23 kilometric cost varies between 0.5€/km and 4€/km. Recall the vehicles compute the utility of re-
 24 locating to region i as the difference between the expected revenue from a ride starting in i (which
 25 depends on the ride occurrence probability p^k , the base fare f_b , the mileage fare f_{km} and expected
 26 ride distance) and the relocation costs to i . Analytically, the ratio $\frac{f_b}{f_{km}}$ defines the maximum dis-
 27 tance vehicles would be willing to relocate if the expected ride distance was 0 km and vehicles got



(a) Evolution of no. passengers served

(b) Evolution of passengers waiting time

FIGURE 18: Evolution of service quality with demand uncertainty and rebalancing costs

		Rebalancing cost					
		0.50	1.00	1.50	2.00	3.00	4.00
Demand uncertainty	0.1	1.01	1.16	1.33	1.42	1.47	1.52
	0.2	1.01	1.18	1.37	1.44	1.48	1.52
	0.3	1.03	1.19	1.39	1.45	1.49	1.52
Relative increase (%)		1.94	2.82	3.98	2.48	0.95	0.11

TABLE 5: Impact of demand uncertainty and rebalancing cost on passengers average waiting time in minutes

1 paid with the base fare f_b only. As f_b is set to 2.2€, a rebalancing cost f_{km} varying between 0.5
 2 and 4€/km implies that vehicles would relocate at most 0.5 to 4.4 km in such conditions.

3 *Service performances*

4 Figure 18 illustrates the evolution of the service quality with varying demand uncertainty and
 5 rebalancing costs. Figure 18a presents the evolution of the total number of passengers served and
 6 Figure 18b the impact on the average waiting time of passengers before pick-up. The rebalancing
 7 cost is shown to have the most significant effect on these two variables. The increased rebalancing
 8 costs significantly decrease the number of passengers served and increase their average waiting
 9 time by up to 1.5 minutes. When the rebalancing cost is particularly high, vehicles barely relocate,
 10 which explains that the performances are similar to the performance of the *no rebalancing* strategy.
 11 To a lesser extent, the demand uncertainty also decreases the performance of the service. As
 12 shown in Table 5, the demand uncertainty increases significantly when the rebalancing costs are
 13 reasonable and do not prevent vehicles from relocating. Under those circumstances, an increase of
 14 the demand uncertainty from 10 to 30% can increase the passengers waiting time by up to 4%.

15 *Vehicle activities*

16 However, the demand uncertainty more strongly impacts the vehicle’s activities than the service
 17 quality. Figure 19 illustrates the effect of demand uncertainty and rebalancing costs on the average

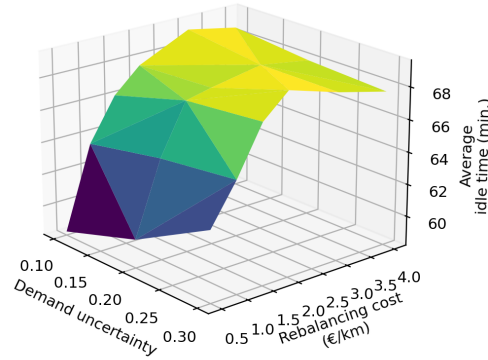


FIGURE 19: Evolution of vehicle average idle time with demand uncertainty and rebalancing costs

1 idle times of vehicles. Unsurprisingly, as it strongly restricts the number of relocating vehicles,
 2 the increase in rebalancing costs reduces the vehicle's activities and contributes to an increase in
 3 the average idle time of vehicles. However, when the rebalancing costs are low, we also more
 4 clearly observe the effect of demand uncertainty on average idle time. For instance, when $c_{empty} =$
 5 0.5€/km , an increase of the demand uncertainty from 10% to 30% contributes to a 7.12% increase
 6 in the idle time of vehicles. The vehicles are more frequently unsuccessfully rebalanced, implying
 7 more significant idle times. In future work, the effect of uncertainty will be assessed on smaller
 8 fleets, *i.e.*, in more tense operation settings. Likely, the demand uncertainty will impact not only
 9 the supply but the demand side.

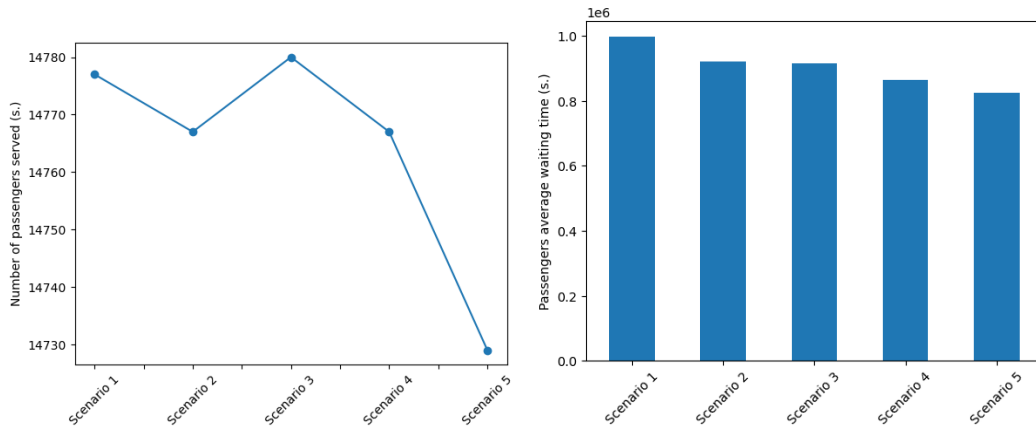
10 **Effect of deposits number and locations**

11 In Section 5.2.2, we discussed the effect of the rebalancing strategy on the traveled distances. We
 12 suggested that the features of the network and locations of the depot could impact it. To measure
 13 this effect, this section compares the service performance of the rebalancing strategy for the five
 14 different depot location scenarios defined in Section 4.2.4.

15 *Service performances*

16 Figure 20 compares the performances of the rebalancing strategy for the different depot mesh
 17 scenarios. Figure 20a compares their performances regarding the number of served passengers,
 18 and Figure 20b looks into passengers' waiting time.

19 Focusing on scenarios 1, 2, and 3, with a single depot per service area, we observe in Fig-
 20 ure 20a that locating them on well-connected nodes (as in scenarios 1 and 3) rather than on the
 21 centroid node (scenario 2) increases the number of passengers served. Additionally, picking the
 22 well-connected node close to the centroid (as in scenario 3) rather than a random well-connected
 23 node (scenario 1) also improves the number of served passengers. Selecting a central depot (sce-
 24 narios 2 and 3) also contributes to reducing the passengers' waiting time (cf. Figure 20b).



(a) Number of passengers served for each depot (b) Passengers average waiting time for each depot mesh scenario

FIGURE 20: Service performances with different depot location strategies

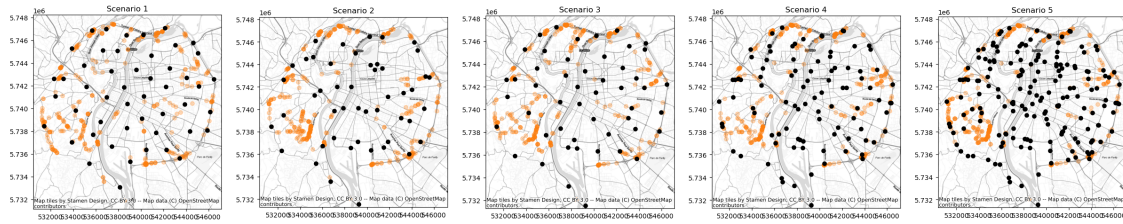


FIGURE 21: Positions of unserved users due to exceeded pick-up time.

1 Interestingly, randomly adding extra depots to Scenario 3, as in Scenarios 4 and 5, does not
 2 allow to increase the number of passengers served. These results should be further investigated,
 3 mainly by generating larger sets of dense networks, but it suggests that a single central depot
 4 position better serves the zonal demand. However, this densification reduces the average waiting
 5 time of passengers because it still drastically reduces the waiting time of many passengers.

6 For each scenario, Figure 21 illustrates where passengers exceeding their pickup waiting
 7 time are located on the network. We observe that most depot locations satisfy the nearby local
 8 demand but that the depot densification is not enough if depots are located downstream
 9 Therefore, the depot positioning strategy should better account for the depot topology and road
 10 section directions.

11 Locating depots on well-connected nodes implies that the demand along corridors or iso-
 12 lated roads suffers from lower satisfaction. In Scenarios 2 to 5, a neighborhood in the southwest
 13 part of Lyon is especially poorly served. The depots of these zones are located quite far away, on
 14 an outer ring road, and distances to reach this neighborhood from there is too large to satisfy the
 15 local demand.

16 Finally, Figure 22 confirms that the location of depots substantially impacts the vehicle
 17 traveled distances per served passenger. Although it does not permit satisfying the same number
 18 of passengers, locating the depot at the region centroid is the scenario with one depot, which limits

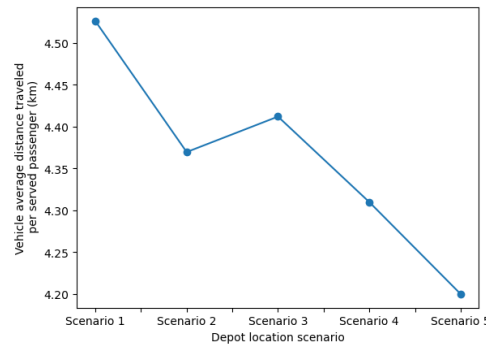


FIGURE 22: Caption

1 the most traveled distance per served passenger. Moreover, as anticipated, increasing the number
 2 of depots per region (Scenario 4 and 5) does contribute to reducing the vehicle kilometers traveled
 3 per passenger.

4 This final study confirms that the service performances and externalities are sensitive to
 5 the depot mesh design. Central and well-connected nodes offer the best performances but do
 6 not suffice to satisfy the demand in some corridors and areas with little accessibility. Densitying
 7 the depot network reduces passengers waiting time and extra kilometers traveled, but locating
 8 these additional depots more strategically seems necessary to ensure a better network and demand
 9 coverage.

10 CONCLUSION

11 Through extensive simulation studies, this paper investigates the performance of an original auc-
 12 tioning process for large-scale ride-hailing fleet rebalancing. The process involves outsourcing
 13 relocating directions from the service to local controllers who negotiate with idle vehicles based
 14 on hypothetical future demand. The distributed Gale-Shapley algorithm is employed to match idle
 15 vehicles with relocation offers.

16 The strategy is applied in the city of Lyon, France, using the trip-based MFD simulation
 17 platform MnMS for fast computing and individual tracking of vehicles and travelers. Simulations
 18 cover four hours of complete morning peak demand, with 15% of the inner demand prioritizing
 19 ride-hailing over private cars. To understand the strategy's performances, the simulations explore
 20 various scenarios, including passenger waiting tolerance, fleet size, demand uncertainty, rebalanc-
 21 ing costs, and depot locations.

22 Results demonstrate a significant impact on the number of passengers served and waiting
 23 time, particularly during demand peaks. Spatial analyses reveal benefits in the suburbs with limited
 24 accessibility and network density. Moreover, the rebalancing strategy ensures a more equitable
 25 distribution of paid activity time among drivers, as indicated by two different inequity metrics.

26 However, the method shows increased distance traveled per passenger served, meaning
 27 additional contribution to road traffic and its externalities. The paper addresses this issue by evalu-
 28 ating different depot location strategies. While a more robust mesh design is needed, this analysis
 29 provides guidelines for improving and developing it.

30 As a continuation of this work, future research will focus on better assessing the effect of
 31 uncertainty, exploring non-uniform uncertainty distribution, and developing local incentive strate-

gies to encourage vehicle relocation to areas with lower accessibility or uncertain demand. Additionally, the performance of the service in ride-splitting and multi-provider operating modes will be assessed.

4 ACKNOWLEDGMENTS

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

7 REFERENCES

1. Beojone, C. and N. Geroliminis, On the inefficiency of ride-sourcing services towards urban congestion. *Transportation Research Part C: Emerging Technologies*, Vol. 124, 2021, p. 102890.
2. Hryhoryeva, M. and L. Leclercq, Competition in Ride-Hailing Service Operations: Impacts on Travel Distances and Service Performance. *Transportation Research Record*, 2023.
3. Wallar, A., M. Van Der Zee, J. Alonso-Mora, and D. Rus, Vehicle Rebalancing for Mobility-on-Demand Systems with Ride-Sharing. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2018, pp. 4539–4546, iSSN: 2153-0866.
4. Simonetto, A., J. Monteil, and C. Gambella, Real-time city-scale ridesharing via linear assignment problems. *Transportation Research Part C: Emerging Technologies*, Vol. 101, 2019, pp. 208–232.
5. Liu, Y. and S. Samaranyake, Proactive Rebalancing and Speed-Up Techniques for On-Demand High Capacity Ridesourcing Services. *IEEE Transactions on Intelligent Transportation Systems*, 2020, pp. 1–8.
6. Alonso-Mora, J., A. Wallar, and D. Rus, Predictive Routing for Autonomous Mobility-on-Demand Systems with Ride-Sharing. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2017, pp. 3583–3590.
7. Miao, F., S. Han, S. Lin, Q. Wang, J. Stankovic, A. Hendawi, D. Zhang, T. He, and G. J. Pappas, Data-Driven Robust Taxi Dispatch under Demand Uncertainties. *arXiv:1603.06263 [cs]*, 2017.
8. Miao, F., S. Han, S. Lin, J. A. Stankovic, H. Huang, D. Zhang, S. Munir, T. He, and G. J. Pappas, 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*, 2015, pp. 100–109.
9. Ramezani, M. and M. Nourinejad, Dynamic modeling and control of taxi services in large-scale urban networks: A macroscopic approach. *Transportation Research Part C*, Vol. 94, 2018, pp. 203–219.
10. C.V. Beojone and N. Geroliminis, Repositioning Ridesplitting Vehicles through Pricing: A Two-Region Simulated Study. In *11th Triennial Symposium on Transportation Analysis Conference (TRISTAN XI)*, Mauritius, 2022.
11. Zhu, P., I. I. Sirmatel, G. Trecate, and N. Geroliminis, Distributed Coverage Control for Vehicle Rebalancing in Mobility-on-Demand Systems. *TRB Annual Meeting*, 2022, pp. 22–03340.
12. M. Seppacher and L. Leclercq, A Decentralised Auction-Based Framework for Rebalanc-

- 1 ing Ride-Hailing Fleets with Uncertain Request Probabilities. In *102nd Transportation*
2 *Research Board Annual Meeting (TRB 2023)*, Washington D.C., USA, 2023.
- 3 13. Manjunath, A., V. Raychoudhury, S. Saha, S. Kar, and A. Kamath, CARE-Share: A Co-
4 operative and Adaptive Strategy for Distributed Taxi Ride Sharing. *IEEE Transactions on*
5 *Intelligent Transportation Systems*, 2021, pp. 1–17.
- 6 14. Wu, Y. H., L. J. Guan, and S. Winter, Peer-to-Peer Shared Ride Systems. In *GeoSensor*
7 *Networks: Second International Conference, GSN 2006, Boston, MA, USA, October 1-*
8 *3, 2006, Revised Selected and Invited Papers* (S. Nittel, A. Labrinidis, and A. Stefanidis,
9 eds.), Springer, Berlin, Heidelberg, Lecture Notes in Computer Science, 2008, pp. 252–
10 270.
- 11 15. Gale, D. and L. S. Shapley, College Admissions and the Stability of Marriage. *The Ameri-*
12 *can Mathematical Monthly*, Vol. 69, No. 1, 1962, pp. 9–15.
- 13 16. Brito, I. and P. Meseguer, Distributed Stable Matching Problems with Ties and Incomplete
14 Lists. In *Principles and Practice of Constraint Programming - CP 2006* (D. Hutchison,
15 T. Kanade, J. Kittler, J. M. Kleinberg, F. Mattern, J. C. Mitchell, M. Naor, O. Nier-
16 strasz, C. Pandu Rangan, B. Steffen, M. Sudan, D. Terzopoulos, D. Tygar, M. Y. Vardi,
17 G. Weikum, and F. Benhamou, eds.), Springer Berlin Heidelberg, Berlin, Heidelberg, Vol.
18 4204, 2006, pp. 675–679.
- 19 17. Ostrovsky, R. and W. Rosenbaum, Fast Distributed Almost Stable Matchings. In *Pro-*
20 *ceedings of the 2015 ACM Symposium on Principles of Distributed Computing*, ACM,
21 Donostia-San Sebastián Spain, 2015, pp. 101–108.
- 22 18. LICIT-ECO7 Lab, Univ. Gustave Eiffel, Lyon, France, *MnMS (Multimodal Network Mod-*
23 *elling and Simulation)*, 2023.
- 24 19. Mariotte, G., L. Leclercq, and J. A. Laval, Macroscopic Urban Dynamics: Analytical and
25 Numerical Comparisons of Existing Models. *Transportation Research Part B: Method-*
26 *ological*, Vol. 101, 2017, pp. 245–267.
- 27 20. Leclercq, L., A. Sénécat, and G. Mariotte, Dynamic Macroscopic Simulation of On-Street
28 Parking Search: A Trip-Based Approach. *Transportation Research Part B: Methodologi-*
29 *cal*, Vol. 101, 2017, pp. 268–282.
- 30 21. Mariotte, G., L. Leclercq, S. Batista, J. Krug, and M. Paipuri, Calibration and Validation
31 of Multi-Reservoir MFD Models: A Case Study in Lyon. *Transportation Research Part B:*
32 *Methodological*, Vol. 136, 2020, pp. 62–86.